FILIPE ANDRÉ DE SOUSA FIGUEIRA BARATA

Licenciado

Control in Distribution Networks with Demand Side Management

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Orientador: Prof. Doutor Rui Alexandre Nunes Neves da Silva, Professor Auxiliar, Faculdade de Ciências e Tecnologias da Universidade Nova de Lisboa

Júri:

Presidente: Prof. Doutor Jorge Joaquim Pamies Teixeira

Arguente(s): Prof. Doutora Teresa Maria de Gouveia Torres Feio Mendonça

Prof. Doutor João Francisco Alves Martins

Vogais: Prof. Doutor José Manuel Prista do Valle Cardoso Igreja

Prof. Doutor Miguel José Simões Barão

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Abstract

The way in which electricity networks operate is going through a period of significant change. Renewable generation technologies are having a growing presence and increasing penetrations of generation that are being connected at distribution level. Unfortunately, a renewable energy source is most of the time intermittent and needs to be forecasted.

Current trends in Smart grids foresee the accommodation of a variety of distributed generation sources including intermittent renewable sources. It is also expected that smart grids will include demand management resources, widespread communications and control technologies required to use demand response are needed to help the maintenance in supply-demand balance in electricity systems. Consequently, smart household appliances with controllable loads will be likely a common presence in our homes. Thus, new control techniques are requested to manage the loads and achieve all the potential energy present in intermittent energy sources.

This thesis is focused on the development of a demand side management control method in a distributed network, aiming the creation of greater flexibility in demand and better ease the integration of renewable technologies. In particular, this work presents a novel multi-agent model-based predictive control method to manage distributed energy systems from the demand side, in presence of limited energy sources with fluctuating output and with energy storage in house-hold or car batteries. Specifically, here is presented a solution for thermal comfort which manages a limited shared energy resource via a demand side management perspective, using an integrated approach which also involves a power price auction and an appliance loads allocation scheme.

The control is applied individually to a set of Thermal Control Areas, demand units, where the objective is to minimize the energy usage and not exceed the limited and shared energy resource, while simultaneously indoor temperatures are maintained within a comfort frame. Thermal Control Areas are overall thermodynamically connected in the distributed environment and also coupled by energy related constraints. The energy split is performed based on a fixed sequential order established from a previous completed auction wherein the bids are made by each Thermal Control Area, acting as demand side management agents, based on the daily energy price. The developed solutions are explained with algorithms and are applied to different scenarios, being the results explanatory of the benefits of the proposed approaches.

Keywords: DMPC, MAS, intermittent energy resource, DSM, energy auction, thermal control areas, shifting loads, energy efficiency;

Resumo

A forma como as redes elétricas operam está a atravessar um período de transformação significativa. As tecnologias de geração renováveis possuem uma presença crescente e a penetração desta geração ao nível da distribuição está a aumentar. Infelizmente, uma fonte de energia renovável é na maioria do tempo intermitente e necessita de algum tipo de previsão e antecipação de comportamento.

As têndencia actuais redes elétricas inteligentes preveêm que estas irão acomodar de uma forma integrada, formas de armazenamento de energia e uma variedade de fontes de geração distribuídas incluindo fontes renováveis intermitentes. É também expectável que as redes inteligentes irão incluir sistemas de gestão da procura e a difusão da comunicações e tecnologias de controlo necessários para que a resposta à procura auxilie no equilíbrio entre oferta e demanda em sistemas de energia elétrica. Eletrodomésticos inteligentes serão provavelmente uma presença comum nos nossos lares.

Desta forma, são necessárias novas técnicas de controlo para gerir as cargas por forma a aproveitar todo o potencial energético existente em fontes de energia intermitentes.

Esta tese foca uma metodologia de controlo para gestão da procura em redes distribuídas, para criar maior flexibilidade do lado da procura e facilitar a integração de tecnologias renováveis. Em particular, o trabalho apresenta um novo método de controlo predictivo multi-agente para gestão sistemas de redes de energia distribuídas do lado da procura, quando na presença de recursos energéticos limitados e flutuantes, e com armazenamento de energia em baterias domésticas ou de veículos. Especificamente, é aqui apresentada uma solução para conforto térmico que gere um recurso energético limitado e partilhado numa perspetiva de gestão da procura, utilizando uma abordagem integrada que envolve um leilão de preço de energia e um esquema de alocação de cargas domésticas.

O controlo é aplicado individualmente a um conjunto de Áreas de Controlo Térmico, *unidades de demanda* (consumidores), onde o objetivo é minimizar a utilização de energia sem exceder o recurso partilhado e limitado enquanto, simultaneamente, a temperatura interior é mantida dentro da zona de conforto. Em ambiente distribuído, as Áreas de Controlo Térmico estão geralmente termodinamicamente ligadas e também acopladas pela restrição energética. A distribuição da energia é efetuada com base numa ordem sequencial fixa estabelecida por um leilão onde cada uma das Áreas de Controlo Térmico, atuando como agentes de gestão da procura, faz as suas licitações com base no preço diário da energia. A solução desenvolvida é explicada por algoritmos e aplicada a diferentes cenários onde os resultados obtidos ilustram os benefícios da abordagem proposta.

Palavras chave: Controlo Predictivo Distribuído, Sistemas Multi-Agente, recurso de energia intermitente, gestão da procura, leilão de energia, áreas de controlo térmico, alocação de cargas, eficiência energética;

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List of Acronyms and Abbreviations

AMI	Advanced Metering Infrastructure
ARMAX	Autoregressive–Moving-Average Model with exogenous inputs model
CPP	Critical Peak Pricing
DER	Distributed Energy Resources
DG	Distributed Generation
DMS	Distribution Management System
DR	Demand Response
DMPC	Distributed Model Predictive Control
DSM	Demand Side Management
EMS	Energy Management System
FLSC	Feasible Loads Schedule Combinations
GPC	Generalized Predictive Control
HVAC	Heating Ventilation and Air Conditioning
I&C	Interruptible and Curtailable Load
IL	Interruptible Load
LQPC	Linear-Quadratic predictive control
LTI	Linear Time Invariant
MAS	Multi Agent System
MBPC	Model Based Predictive Control
MIMO	Multiple-Input Multiple-Output
MO	Market operator
MPC	Model Predictive Control
MUSMAR	Multistep Multivariable Adaptive Regulator
OCGT	Open Cycle Gas Turbine
PEV	Plug-in Electric Vehicle

PLC	Power Line Communication
PLSC	Possible Loads Schedule Combinations
PTR	Peak Time Rebate
RES	Renewable Energy Sources
RHC	Receding Horizon Control
RTP	Real Time Pricing
SGPC	Stable Generalised Predictive Control
SISO	Single-Input Single-Output
TCA	Thermal Control Area
TCL	Thermostatically Controlled Loads
TOU	Time Of Use
ZOH	Zero-Order Hold

Chapter 1

Introduction

1.1 Introduction

Traditional electric power systems consist of large power generating plants, interconnected via a high-voltage transmission lines, loading serving entities which deliver power to end users at lower voltages using local distribution networks.

Importance of distributed generators (DGs) has increased significantly over the past few years due to its potential for increasing reliability and lowering the cost of power through the use of on-site generation. Development of small modular generation technologies, such as photovoltaic, wind turbines and fuel cells has also contributed to this trend. However, novel operational and control concepts are needed to make a proper integration into the power grid system. Control strategies must be further developed to achieve the targeted benefits while avoiding negative effects on system reliability and safety. The current power distribution system was not designed to support distribution generation and storage devices at the distribution level; compatibility, reliability, power quality, system protection and many other issues must also be considered before the benefits of DGs can be fully obtained (Al-Hinai & Feliachi 2009).

A new emerging type of grid will soon be a reality. Smart Grids (SGs) are planned to include decentralized generation, active network management for generation and storage, where the actions of all connected agents to the electricity system can be intelligently integrated aiming for a sustainable, efficient and secure energy supply system. Future SGs are anticipated to support a variety of DG, including intermittent renewable sources (James & Jones, 2010).

Smart Grid concept is built on many of the technologies already used by electric utilities but adds additional communication and control capabilities optimizing the operation of the entire electrical grid. Smart Grid is also positioned to take advantage of new technologies, such as hybrid plug-in electric vehicles (PEV), various forms of distributed generation, solar energy, smart metering, lighting management systems, distribution automation and many more.

In a scenario with strong presence of intermittent renewable energy sources (RES) that supply a set of houses, the new techniques must developed to deal with smart devices, energy management systems (EMS) such as programmable controllable thermostats and/or PEV charge, and be capable of making intelligent decisions based on smart prices and users comfort. Therefore, it is crucial to take into account a global solution that is able to take advantage of these features.

1.2 Background

Since the beginning of electricity grids, demand has fluctuated and supply has been provided to follow along. The intermittency of RES, such as wind or solar generation, stills nowadays the major challenge for the integration of these resources. The present trend in power systems is to connect more and more RES increasing significantly the security and the quality of supply.

One of the most common solutions to mitigate the problem is operating energy sources, such as gas turbines or hydro power plants, balancing the variations. But, when the variations are significant and change rapidly, the backup source needs to be higher and faster, leading to increased carbon emissions. Also, widely used the frequency regulation is the direct measure of the balance between generation and system demand at any one instant, and must be maintained continuously within narrow statutory limits.

Another solution is the energy storage (Ribeiro et al. 2001; Koeppel & Korpas, 2006), if there is a surplus in energy produced it is fed into the storage. Energy storage is especially critical when managing the output of intermittent renewable resources, ensuring their generation capacity is available when needed most, maximising their value, but presently technology available does only provide answers in low generation time intervals. For example, depending on the size of the battery pack, electric cars may store enough electricity to power a house for a few hours, and with small modifications, car batteries can deliver stored power to a home and to the power grid.

As showed there are several solutions to overcome the issue of intermittency but all have problems to be overcome. The desirable approach is that the demand should follow the source, passing the control to the demand side, having demand side management (DSM) (Callaway, 2009; Hamidi, 2007). Due its benefits to consumers, enterprises, utilities and society, in the last decades, many efforts have been made to having demand play a more active role in balancing the system. DSM benefits are related with customer energy bills and peak power prices decrease, reduction in the need for new power plants, transmission and distribution, reduction in air pollution and with a significantly increased in energy efficiency. With the growing interest in intermittent RES use, new opportunities and challenges are triggering and obliging these efforts to come true. Because of technology barriers and lack of automation, the traditional way of implementing DSM is via price incentives, i.e. by lowering tariffs at times when the aggregated demand is expected to be below average, so as to encourage the end user to shift flexible loads towards these periods (Saffre, 2010). But, with the new technologic advances and world trends around the SGs concept (Chebbo, 2007; Commission, 2006), and requiring this kind of grid intelligent control and management based on advanced communication, monitoring solutions, automation and metering, novel opportunities and challenges to DSM are emerging.

In the smart world, simple household appliances like dishwashers, clothes dryers, simple electric heaters or heating ventilation or air conditioning (HVAC) systems are planned to be fully controllable to achieve the network maximum efficiency. Renewable energy sources are expected to be a common presence and all kWh provided by these technologies should be efficiently applied. Active demand side management provide solutions to control the loads, adapting them to the current RES.

Being an actual theme, and despite the present trends and R&D efforts, SGs are still in the “implementation phase”. More research is needed to provide solid solutions to overcome all the constraints and turn into reality this ambitious vision. Smart Grids involve a mix of concepts: distributed generation, DSM, intelligent control, energy efficiency, intermittent RES, thermal comfort, load control and energy saving are some of them which are interconnected and should be integrated into solutions. Smart Grids are, therefore, the most efficient approach to integrate DG and RES in a coordinated way with demand management in a sustainable system (Blanquet et al., 2009). To take advantage from the innovative technology characteristics provided by future smart grid, it is necessary the development of new models and control techniques which can support and manage all the mentioned concepts and, at the same time, deal with the network complexity and its distributed nature (Werbos, 2011).

1.3 Motivation

Currently buildings account for 40% of the world’s energy consumption and almost half of the today’s greenhouse gas emissions. This means buildings contribute to more greenhouse gases emissions than traffic; which is estimated at 31%. Industry is estimated at 28%. When we breakdown and analyse building’s energy consumptions, the most worrying aspect is that most of this energy is used for heating or cooling (StorePET, 2014).

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In Europe, the energy use in buildings has overall seen a rising trend over the past 20 years. For example, in 2009, households were responsible for 68% of the total final energy use in buildings, mainly due to space heating responsible for around 70% (Nolte, 2011). This increasing energy consumption is mainly to fulfil the demand for thermal comfort, being presently the HVAC systems the principal energy end use in buildings (Korolija et al., 2011). By these facts, it is socially, environmentally and economically imperative to decrease the energy consumption by increasing the buildings efficiency. A viable choice to achieve the reduction of energy consumption in the building sector is the application of demand response (DR) mechanisms. Demand Response program, is an efficient load management strategy for customer side, it is nowadays mostly used with the encouragement of customers to shift their habits wisely according to electricity price variation during daytime (Siano et al., 2014). The DR potential it is not sufficiently explored, being the two key challenges to work with diverse heterogeneous loads and with the distributed nature of renewable sources. New technology advances in communication are providing solutions to overcome the current electricity demand requirements. This new development has accelerated devising various industrial programs for scheduling utilization of residential appliances (Wang et al., 2015). This DR mechanisms combined with DSM methodologies will be relevant in the future distributed SGs (Mahmood et al., 2014), and provide solutions that allow buildings to be fully integrated and prepared to efficiently coexist in an dynamic and inconstant environment typically supported by renewable resources (Figueiredo et al, 2010). Nowadays the production of electricity system follows the load. However, the renewable sources of electricity are essentially intermittent and it is vital to provide flexibility to the grid to absorb the variations from these sources. In the intelligent energy system (Smart Grid) the production controls the consumption. For example, when the wind blows or the sun shines, buildings consumption must be automatically adjusted and consumers will go from being passive participants to be active players in the electricity system. Several solutions are emerging to deal with the variability, flexibility and poor controllability of the green sources and consequently on the ability to maintain the balance between demand and supply. Remark that, DSM strategies must have into account the control of many kinds of appliances, for instance, HVAC systems, lighting or electric vehicles charging.

The methodology here presented seeks a solution to respond to this variability, implementing, with the technological and advanced environment that SGs are projected to provide (Paul et al., 2014), pursuing new technologies and solutions that will allow simple home appliances to be entirely controllable. Also, this active DSM is able manage the loads to obtain harmony in demand supply ratio.

1.4 Research Questions

With SGs, domestic customers will pass from static consumers into active participants in the production process. Final user's participation can be achieved due to the development of new domestic appliances with controllable load. Shifting their electricity consumption in time or, by changing their work conditions, these devices can be controllable, adjusting the demand to the desired intermittent source without decreased the comfort of the residents. In distributed networks, aggregated to an intermittent source, an unlimited number of this kind of loads can exist, representing a control problem to achieve the network efficiencies, involving stakeholder's satisfaction. To incorporate this in system design and analysis, demand response needs to be supported by scientific methodology based on analysis and models verifiable by experiment. How to improve energy efficiency using this domestic potential is still not well studied and needs to be a research topic.

Considering the mentioned above, this work aims providing solutions to answer the following research questions:

Q.1 ***How, in a distributed network, can the demand be adjusted to an intermittent source to maximize the energy efficiency***?

Q.2 ***How to improve energy efficiency using the domestic potential in a distributed network***?

Q.3 ***Which control methods should be applied in a distributed network with demand side management to obtain all the existing energy potential from intermittent energy sources***?

The adopted work hypothesis to address the research question is defined below:

Using an integrated approach, that in a distributed environment, considers multi-agent control scheme and an optimization MPC multi-objective approach with anticipative effect, capable to deal in a DSM perspective, with fluctuating energy sources, smart load control, thermal comfort and real-time price negotiation.

1.5 Aimed Contributions

The work here presented is distinct and has the advantage of providing a solution that integrates set features and concepts that are also the smart grid bases, such as intelligent control, distributed generation, energy efficiency, energy saving, DSM, fluctuating energy sources, smart load control, thermal comfort, real-time price negotiation and energy auction markets mechanisms. These characteristics deliver a unique structure where the grid connected entities actions can be intelligently combined, aiming for a more efficient, secure and sustainable energy system. So, the work intends to provide an innovative solution involving an integrated

Distributed Model Predictive Control (DMPC) to manage networks that is able to efficiently adapt the consumption to an intermittent renewable source. It provides news developments in DSM with renewable energy sources and backup fossil energy using an hourly auction mechanism access and a load allocation scheme that allows managing the loads in order to balance demand and supply. The proposed sequential multi-agent DMPC scheme for thermal house comfort and energy savings provides robustness, adjustment and flexibility to the global system. Also the work presents an energy usage optimization scheme with DSM in which the consumer as the flexibility to choose by the hour between comfort or energy savings.

The proposed integrated solution provides several scientific contributions that have been developed under the framework of this thesis:

- **C.1 New developments in DSM, for different thermal areas, exploit an integrated optimization approach able to cope with intermittent renewable energy sources and backup fossil energy using an hourly auction mechanism access -** the obtained solution allows managing the loads in order to balance demand and supply. The DSM optimization process uses a routine that finds a constrained minimum of a quadratic cost function that penalizes the sum of several objectives, which based on energy forecasts and several other inputs, is able to adjust the energy consumption to an intermittent renewable resource or even restrict it to this type of resource in detriment of fossil sources. An auction mechanism allows stablishing an access order to the renewable source based on an hourly energy bid. Sequentially, the controllers transmit between them the information about the available energy;
- **C.2 TCA dynamic model with multi-zone dynamically coupled areas is developed -** the developed model is built for infrastructures composed by several adjacent areas that may thermally interact among them. The dynamical model allows each room to be treated independently, with its own construction features, thermal disturbances, comfort requirements, energy costs and consumption needs. When distinct divisions thermally interact the information about the predicted indoor temperature is transmitted between them. This change of information allows to each controller a greater understanding about the surrounding environment and consequently improving the decision-making ability;
- **C.3 A novel sequential scheme for DSM based on multi-agent DMPC for thermal house comfort and energy savings is reported -** the proposed sequential scheme provides robustness, adjustment and flexibility to the global system. The sequence is built based on an energy bid where the highest biddings are placed first in the access order. After consume, each agent predicts its consumption profile and pass throw the next, the information about the predicted available renewable energy. At each hour, the

sequence is established and the energy price depends from the offered bid, amount and type (renewable or grid) of energy consumed;

- **C.4 Shifting load algorithm for loads allocation -** customer sets features of flexible loads and the algorithm fits them in the most favourable time interval gap. Each customer select for each division, the characteristics of the loads, the load value, its duration, the turned on time and the “sliding level” of the “shifted loads”. With this information the algorithm finds all the possible load combinations and from these selects only the feasible ones. The feasibility of the loads is related to the predicted hourly available power, so, at each instant the look forward and tries fitting the loads in gaps that privileges the consumption of renewable energy. Thus, in a distributed environment with energy and comfort constraints, the algorithm is able to find the best hour to turn on the loads;
- **C.5 Energy usage optimization scheme with DSM adjustable parameters -** with the developed optimization scheme the consumer has the flexibility to choose hourly between comfort or energy savings. Each controller provides to the consumer a set of parameterizations which according to his consumption perspective, space occupancy schedule, indoor temperature preferences and energy cost, provides to the user the ability to be hourly in his most convenient state.

1.6 Outline

This dissertation is structured as follows:

Chapter 1 – ***Introduction***, here is performing a brief introduction with a background analysis, followed by the research problem. The chapter also states the main original contributions of the work and in the end the outline of the thesis is presented.

Chapter 2 – ***Literature Review and Model Based Predictive Control***, the focus of this chapter is to perform a background analysis on the main topics of the thesis, Demand Side Management, Multi-Agent-Systems and Model Based Predictive Control. The chapter also includes general review on distributed model predictive control formalization for complex large-scale dynamical systems.

Chapter 3 – ***Dynamic Models and Scenarios Description***, the main ideas and models that support the research developed are presented. The chapter starts by presenting the general abstract problem, the conceptual scenarios and describe the system architecture. Finally, the developed dynamic model is addressed using a line state-space model approach.

The elaboration of this chapter provided relevant matter that was originally included in part in the following publications (Barata et al., 2014a; Barata et al., 2014b).

Chapter 4 – ***MPC and PI control in thermal comfort systems*** chapter presents the fundamental approach towards the final developed structure. Is the first seed which allowed us to understand the problem, its dynamics and to verify that the MPC control strategy is suitable for the objective that is intended to be achieved. The methodologies are based on a predictive control structure associated to a PI controller and applied to the thermal house comfort in an environment with limited energy sources. The predictive control is compared with the traditional control methods used in thermal systems. Also, it was created a temperature "comfort zone" to weight only the temperatures outside the gap, instead of traditional system were all deviations are weight. Simulation results and analysis also complement two distinct situations where the system reacts differently if the indoor temperature is inside or outside the "comfort zone".

The elaboration of this chapter provided relevant matter that was originally included in part in the following publications (Barata et al., 2012a).

Chapter 5 – ***Thermal Comfort with Demand Side Management Using Distributed MPC***, this chapter presents a DMPC methodology for indoor thermal comfort which simultaneously optimizes the consumption of a limited shared energy resource. Firstly, the global scenario and all the made assumptions that support the thesis are described. Also, the implemented sequential architecture scheme is pictured. Secondly, the control objective is defined and the tailored DMPC optimization problem is detailed, formalized and exemplified.

The *Algorithm* I which describe implemented sequential scheme is presented. This algorithm represents the basic structure for more complex schemes.

Chapter 6 – ***DMPC for Thermal House Comfort with Sequential Access Auction,*** this chapter presents the obtained results achieved with the developed integrative methodology to manage energy networks from the demand side with strong presence of intermittent energy sources and with energy storage in house-hold or car batteries.

The results are pictured with and without batteries support and two different approaches are considered, the energy split based on a fixed sequential order, and with the energy split varying hourly based on a bid value directly related with the consumption profile behaviour. The *Algorithm* II, which describes implemented sequential scheme with variable hourly sequence and energy storage, is also presented.

The elaboration of this chapter provided relevant matter that was originally included in part in the following publications (Barata et al., 2012b; Barata et al., 2013a).

Chapter 7 – ***DMPC for Thermal House Comfort with Sliding Load*** chapter presents the developed DMPC integrative solution which is able to, in a distributed network with multiple TCAs, adjust the demand to an intermittent limited energy source, using load shift and maintaining the indoor comfort. The *Algorithm* III which describes the implemented shifting and loads allocation scheme is presented followed by the results and its analysis. The elaboration of this chapter provided relevant information that was included in the following publications (Barata et al., 2013c) and more detailed in (Barata et al., 2014c).

Chapter 8 – ***Conclusions and Future Work Directions***, in this last chapter, discusses the main conclusions of this work, detailing the problems found along the way and pointing out potential solutions for them. Additionally, the main results and contributions are summarised, and some possible directions for further research are mentioned.

Chapter 2

Literature Review and Model Based Predictive Control

2.1 Introduction

Future SGs are expected to include distributed generation, demand side management, intelligent control, energy efficiency, intermittent RES, thermal comfort, load control, real-time price negotiation and energy saving (IEA, 2011). These concepts are the smart grid bases, where the actions of all agents connected to the electricity system can be intelligently integrated aiming for a sustainable, efficient and secure energy supply system.

Being an actual theme, and despite the present trends and R&D efforts, SGs are now giving the firsts steps in the implementation phase, Figure 2.1, with small projects and grid prototypes all over the world (EcoGrid, 2014; DOE, 2014). More research is needed to offer solid solutions to overcome all the constraints and turn real this ambitious vision.

In a scenario with strong presence of intermittent RES that supply a set of houses, it is possible to manage several loads in each house in order to: 1) adjust the demand to the supply; 2) maintain indoor thermal comfort; 3) achieve lower energy costs 4) reduce CO_2 emissions. Using a demand side management approach, the distributed loads can be manage by negotiating in real time the energy price and the consumer comfort in order to guarantee the balance between demand and the intermittent source. The main goal is to develop new control methods and methodologies to manage future SGs with demand side management with high penetration of intermittent resources.

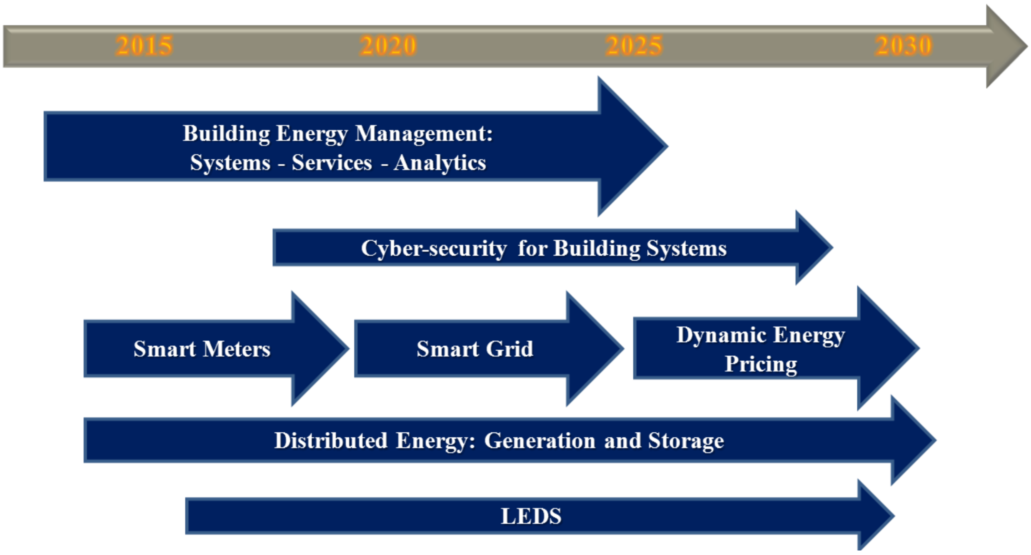

Figure 2.1. Smart Grid Roadmap (Bsria, 2014)

The method uses the match results between demand and supply to decide the control actions to be implemented on the demand side. It is considered environmental and pre-establish variables as a decision-making factor. By using this active DSM control, the optimal control strategies for various appliances can be generated whilst maximum utilisation of energy supplied from intermittent systems is guaranteed. In a distributed network, with several loads at different locations control actions applied for solving a local energy problem can create lack of energy at a different location in the network. Therefore, coordination control strategies are required to make sure that all available control actions serve the same objective. To support the idea, it is consider multi-agent control schemes in which each agent will employ a model-based predictive control approach. The agents communicate and negotiate in a distributed network environment, to improve decision making, and, by adjusting the demand to the source, the maximum energy potential existent in the intermittent source can be achieved.

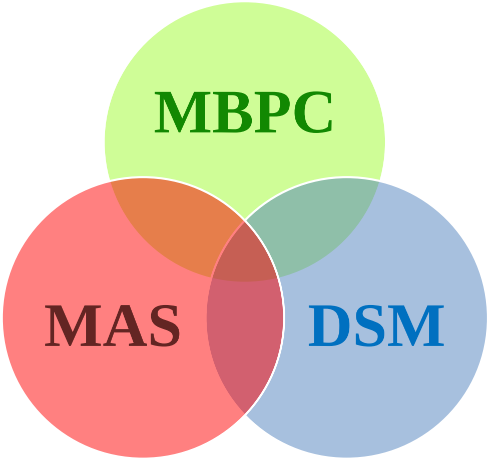

Figure 2.2. Venn diagram with implemented technologies.

At the same time, as referred, is also desirable no or negligible impact on end users/occupiers. Thus, this literature review intend to show what are the main research trends related with the three main support ideas that interact in this work, DSM, Multi-Agent Systems (MAS) and Model Based Predictive Control (MBPC), Figure 2.2.

2.2 Demand Side Management for Distribution Networks

To reach important reduction in CO_2 emissions, the RES will be the main contributors to the electricity generation systems. Presently, the solar and wind power, are the renewable energy technologies that are commercially available with sufficient scalable. Although the expected growth of these sources through to 2020 target is envisioned, there are real concerns about the variability, flexibility and poor controllability of the sources and consequently on the ability to maintain the balance between demand and supply. The growing uncertainty in power systems coupled with the introduction of power markets calls for the development of new tools for planning, operations and market-based decision-making. To deal with this uncertainty due to the dissemination of renewables, the systems will need, for example, to apply bigger amounts of reserve that is generally provided by a combination of synchronised and standing reserve. Besides to synchronise reserve provided by part-loaded plant, the balancing task will also be supported by standing reserve, which is supplied by a plant with higher fuel and environmental costs, such as Open Cycle Gas Turbine (OCGT), or through more desirable techniques such as storage facilities or DSM.

Demand Side Management was introduced in USA by Electric Power Research Institute (EPRI) in the 1980s (Balijepalli et al., 2011) and has been traditionally seen as a means of reducing peak electricity demand so that energy suppliers could diminish the construction of new capacity. Therefore, to decrease peak load, DSM is mainly applied via price incentives, with the existence of lowering tariffs at times when the aggregate demand is expected to be below average to encourage the end user to shift flexible loads towards those periods. By reducing the overall load on an electricity network, DSM provides numerous benefits: increasing system reliability, reducing of the dependency on energy importation, reducing energy prices, stimulates energy markets competitively, reducing harmful emissions to the environment and in avoiding high investments in generation, transmission and distribution networks. Thus DSM applied to electricity systems provides significant financial, reliability and ecological benefits. With the power markets development, new emerging technologies and the new power grid concepts (microgrid, smart grid), innovative solutions are giving more relevance to DSM strategy. Generally, DSM programs are separate in these four categories:

- **Energy efficiency**, the user decreases the demand for energy without sacrificing the benefits received from energy (e.g. installing building insulation, purchasing more efficient appliances);
- **Conservation**, the consumer decreases his energy demand by reducing their energy usage (e.g. adequate thermostat temperatures, turning off lights);
- **Load management**, the energy demand is reduced during periods of peak demand when capacity is limited and the cost of energy provision is high;
- **Public information**, which encourages customer participation in energy efficiency, conservation, and/or load management activities through public campaigns, direct to customer communication, or increasing customer access to information about their consumption of energy services.

DSM directly benefits utilities in the following ways:

- Distribution - only utilities avoid having to purchase additional peaking and base-load energy resources. From the volatile wholesale energy market;
- Electricity generating utilities avoid the cost of securing fuel and pollution abatement for peaking and base-load power plants, while deferring expensive investments in new power plants and their associated compliance costs;
- Both kinds of utilities avoid costly investments in new transmission and distribution infrastructure.

Utilities may in turn pass these savings on to consumers, resulting in lower utility bills. In addition, DSM directly benefits utility customers in the following ways:

- Many DSM programs provide financial incentives (such as rebates, bill credits, lower rates, or low interest financing) to encourage customers to make choices that reduce their energy consumption overall or during periods of peak demand;
- By encouraging customers to reduce their energy usage or to consume energy during times when energy services are less costly, DSM programs help customers to reduce their monthly utility bill.

Demand response is a class of DSM programs in which electricity companies offer incentives to clients to reduce their demand for electricity during periods of critical system conditions or periods of high market power costs. DR programs are normally classified according to the customer motivation method and the criteria with which load reduction "events" are triggered or initiated. So, when the utility offers customers payments for reduction of demand during specified periods, the program is called *load response*. But, when customers voluntarily reduce their demand in response to forward market prices, the program is called *price response*. Customers reduce load during those periods when the cost to reduce load is less than the cost to generate or buy the energy. In this context, brief descriptions of these DR techniques that are presently worldwide being applied and studied are now described.

Load-Response Programs

In load-response programs, utilities offer customers payments for reducing their electricity demand for specified periods of time.

- Direct load control

Direct load control is applied to domestic appliances that can be switched on and off during periods of time using remote appliance controllers. The most common applications are the ones that account for the most significant portion of energy demand, HVAC systems and water heaters;

- Load limiters

Load limiters have the intent to limit the power that can be used by consumers. This approach temporarily disconnects parts of the installation, most often the HVAC or electrical heating during power peaks. This scheme can also provide some flexibility to users to decide which appliances to use now and what can be delayed;

- Interruptible and Curtailable Load (I&C)

Interruptible and Curtailable-load programs are relatively simple to implement, the customers agree to decrease or turn off pre-established loads for a period of time when notified by the utility. Clients can switch off loads or adjust settings. Utilities must notify customers before an interruptible/curtailable load event. As reward, participants receive lower electricity bills during normal operation, as well as additional incentives for each event;

- Frequency regulation

System frequency is the direct measure of the balance between generation and system demand at any one instant and must be maintained continuously within narrow statutory limits. Recently, there have been initiatives to investigate a technology that can be incorporated into electrical appliances to provide frequency regulation (Dynamic Demand, 2014);

- Scheduled Load

Scheduled load reductions are pre-planned between the utility and customer. Clients receive bill reductions, as well as significant advance notification, since contractual agreements are set months ahead. The advantage of this program is that customers can plan to reduce load on pre-determined days;

Price-Response Programs

These programs allow customers to voluntarily reduce their demand in response to economic signals.

- Time of use pricing

Time of use (TOU) tariffs are designed to more closely reflect the production and investment cost structure, where rates are higher during peak periods and lower during off-peak periods. Basically, instead of a single flat tariff for energy use, TOU tariffs are plan to be higher when electric demand is higher, meaning that when you use energy is as important as how much you use. These programmes are commonly practiced in a large number of countries, particularly for households with electric heating;

- Dynamic/Real Time Pricing (RTP)

The dynamic imposed by the existing deregulated market is based on real time system of supply and demand. Prices change time to time and hour to hour depending upon these two factors. By exposing customers to RTP i.e. time-varying prices, they can have a better view of the prevailing market and the information and incentive to reduce their demand at peak times or critical peak prices (CPP) and by this way provide a financial incentive for participants to shift optional activities, such as clothes washing and drying and dishwashing, to times other than critical peak periods;

- Demand bidding

Demand bidding programmes are available when the customer is willing to negotiate is consumption needs in detriment of cost reductions. So, the client is disposed to decrease or sacrifice his consumption of electricity at a certain predetermined price. For example, this technology can be applied to a smart thermostat which controls the indoor comfort equipment’s. So, depending from real time electricity price levels, the thermostat can be programed to allow different sceneries in different schedules.

In buildings, novel solutions that integrate occupant behaviour within the building in relation to energy consumption are emerging (Virote & Neves-Silva, 2012).

Only with smart metering and smart appliances technology the mentioned programs are viable. With smart meters consumer can see exactly what power loads are driving up their energy use and make specific changes, (Navetas, 2014). This information combined with time flexible smart electrical appliances (HVAC systems, water heaters, refrigeration, lighting, etc.) can lead to much better energy efficiency.

As showed, DSM will have an important role in the future smart grids architecture (Chen et al., 2010; Luo et al., 2010) and by this reason many studies are being performed involving the mentioned DSM techniques to provide future implementation solutions.

Callaway (2009), with the goal of delivering services such as regulation and load following, developed new methods to model and control the aggregated power demand from a population of thermostatically controlled loads (TCLs). The researcher manipulates the temperature set point in order to control the demand curve and adapt it to a wind plant power source. The work showed that it is possible the demand to follow the source with small changes in the nominal thermostat temperature set point. With similar objective, Jun (2009), developed an algorithm capable of controlling loads based on the available supply at certain time. The objective of the algorithm is to minimize the impact on users and at the same time maximize the match between demand and supply through identifying the best combinations of different demand side control options such as load shifting, load control (on/off control and proportional control) and load recover for various demand loads.

A potential application for controllable domestic heat loads, and flexible distributed generation in power systems with significant capacities of uncertain wind generation is described in (Savage et al, 2008). Heat load is effectively controlled by remote adjustment of thermostat set points. The system transmit a signal to reduce heating load set points when net demand is greater than the forecast value and a reserve shortfall was imminent. Zaidi et al., (2010) follows a DSM approach, where unessential loads get selectively disconnected from the grid in an under-generation scenario. In order to automatically detect unessential loads, load recognition on the basis of measured consumption data can be performed. With the same objective of peak shaving and balance between demand and supply, (Molderink et al., 2010), shows that with the use of good predictions, in advance planning and real-time control of domestic appliances, better matching of demand and supply can be achieved. With a similar approach, several other studies can be found (James & Jones, 2010; Krishnappa, 2008).

As presented, several methods are focus in the development of load control manipulation models, however, DSM is also been studied via models that use electricity incentive prices to promote load management (Yang et al., 2006; Hamidi et al., 2008; Aalami et al., 2008; Yu & Yu 2006; Shaikh & Dharme, 2009).

The desire DSM methodology that is intended to be achieved is a mix of these two solutions. It intends to take advantage from the innovative technology characteristics provided by future smart grids. It is expected that every electric house appliance will be controllable and the communication infrastructures will allow RTP arrangement. At the same time, is desirable to maximize the efficiency of renewable energy resources and minimize the consumer energy costs. New models and control techniques must be developed to be capable of not only to manage loads based on the available supply at a certain time, but also by negotiating in real time the energy price and the consumer comfort (without significantly compromising the user satisfaction) in order to guarantee the balance between demand and the intermittent source.

In a scenario with strong presence of intermittent RES that supply a set of houses, the new solution must include smart devices, energy management systems (EMS) such as programmable controllable thermostats and/or PEV charge, capable of making intelligent decisions based on smart prices and users comfort.

2.3 Model Based Predictive Control

The firsts predictive controllers concepts were born from optimal control methodologies, such as the Linear Quadratic (LQ) or the Linear Quadratic Gaussian (LQG) controllers in the early'70s (Anderson and Moore, 1971). Only in late 70's that the first two truly MPC control laws arise, the Identification-command (IDCOM) and the Dynamic Matrix Control (DMC), which are acknowledged as the roots of MPC. These two methods share some common features which established the basis of MPC.

The predictive control based on model MBPC is nowadays as one of the most popular and efficient control strategies in industry. So, during the last two decades a growing interest has been granted to model predictive control (MPC) due to its ability to handle constraints in an optimal control environment (Moroşan et al., 2010; Mosca, 1995). It is expected that soon MPC may substitute the majority of the classic controllers that are becoming inefficient in complex environments.

MPC is a form of control in which the current control action is obtained by solving on-line, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state, the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant. The major advantages that have contributed for the success of this method are (Orukpe 2005; Jimenez 2000):

- It handles multivariable control problems naturally, Single-Input/Single-Output SISO) and Multiple-input/Multiple-Output (MIMO) formulations are similar;
- Difficult dynamics such as dead-times, unstable or non-minimum phase systems can be easily handled;
- Feedforward compensation of measurable disturbances can be introduced in a natural way exploiting the model-based and predictive features of the MPC methodology by using disturbance models;

- It can take account of actuator limitations The incorporation of constraints in the manipulated and controlled variables and/or states is a simple task. Constraints can be considered at the controller design stage and the resulting optimisation problem can often be solved using standard Linear Programming (LP) or Quadratic Programming (QP) tools. It also allows operation closer to constraints, hence increased profit;
- MPC controllers have been developed either for linear or non-linear models;
- Methods which guarantee the stability of the closed-loop system are available;
- Robustness features can be enhanced through tuning parameters or optimisation methods. Constraint handling is, indeed, one of the most appealing properties of MPC, since limits of several kinds always occur in practice.

Constraints can be used to describe several security limits, physical restrictions, technological requirements and so on. These requirements must be handled at the controller design stage to avoid undesirable performance. Constraints have two main objectives. They can be used to increase the accuracy of the model, incorporating on it the actuator and plant limits and also be used as tuning knobs to describe control requirements or specifications. Typically, optimal operating point lies close to (or on) one or several limits and therefore, representing an advantage from an economical point of view when it operate as close to the constraint boundary as possible. Constraints can be classified according to different criteria. The following classification of constraints, according to practical considerations, is due to Álvarez and de Prada (1997):

- Physical constraints. These limits, which must never be surpassed, are determined by the physical limitations of the system;
- Operating constraints. These bounds are fixed by the plant operators to specify the optimal operating region. The operation constraints are more restrictive than he physical limits;
- Optimization or set point conditioning constraints. These limits, more restrictive than the operating constraints, are used only if the set point conditioning technique is applied;
- Working constraints. These are the actual constraints considered by the controller to determine the feasible region. The working constraints are obtained by choosing the most restrictive among the physical, the operating and the optimization limits. Apart from constraint handling, the relevant issues of stability and robustness have been successfully tackled in the last decade.

The MPC block diagram is present in Figure 2.3 where the main blocks represent:

Reference Trajectory - represents the desire signal to future outputs. The previous knowledge of this trajectory provides the anticipative effect of this controller;

Model - the mathematical model, linear or nonlinear, that represents the process must be capable to describe its dynamic behavior with sufficient accuracy;

Predictor- trough the mathematical model provides the future outputs based on the actual plant information;

Optimizer - minimizes the cost function at every time sample to obtain the control action that guaranties the system performance. When linear models are used and the problem is unconstraint, the quadratic cost function presents a analytical solution, otherwise, some numeric optimization methods must be used.

As can be seen, the presence of the plant model is a necessary condition for the development of the predictive control. The success of MPC depends on the degree of accuracy of the plant model (Zheng 2010).

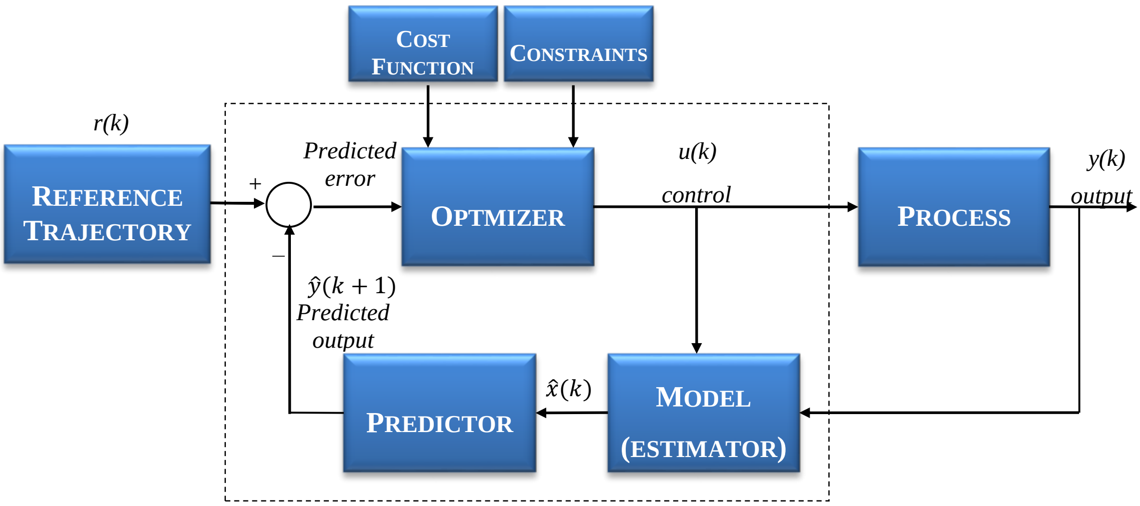

Figure 2.3. Basic block diagram of MPC

Predictive control uses the receding horizon principle. This means that after computation of the optimal control sequence, only the first control sample will be implemented, subsequently the horizon is shifted one sample and the optimization is restarted with new information of the measurements. The prediction horizon remains the same length despite the repetition of the optimization at future instants. Since the state prediction x and hence the optimal sequence $\mathbf{u}^*$ depend on the current state measurements $x(k)$, this procedure introduces feedback into the MPC law, providing a degree of robustness to modelling errors and uncertainty. Figure 2.4 explains the idea of receding horizon.

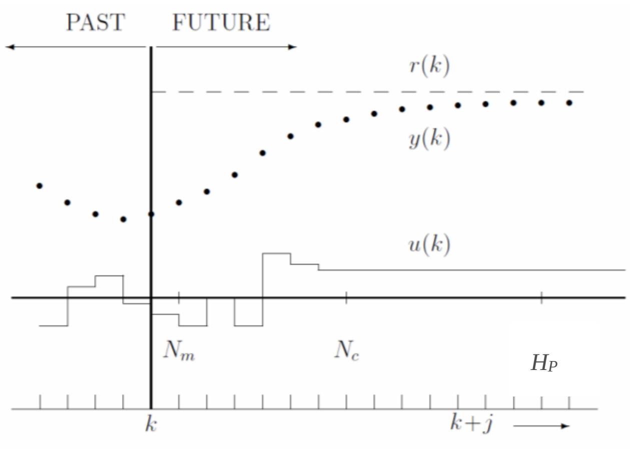

Figure 2.4. Conceptual picture of the moving horizon in predictive control (Boom & Stoorvogel, 2010).

In Figure 2.4 N_m, N_C and H_P represents is the minimum cost horizon, the control horizon and prediction horizon respectively. At time k the future control sequence $\{u(k|k), \ldots, u(k + Nc - 1|k)\}$ is optimized such that the performance-index $J(u, k)$ is minimized subject to constraints. At time k the first element of the optimal sequence $(u(k) = u(k|k))$ is applied to the real process. At the next time instant the horizon is shifted and a new optimization at time k+1 is solved.

The goal of MPC is to minimize a cost function over a given prediction horizon period. This cost function should give an indication for the performance of the system. The control signal contains the setting for the control measures that are able to influence the system, and the constraints may contain the upper and lower bounds on the control signal, but also linear or non-linear equality and inequality constraints on the control inputs and the states of the system.

In MPC, control decisions, system inputs, $u(k)$ are made at discrete time instants k = 0,1,2,..., which usually represent equally spaced time intervals. At decision instant k, the controller samples the state of the system $x(k)$ and then solves an linear optimization problem of the following form to find the control action:

$$\min_{u} J(x, u; x(k)), \tag{2.1}$$

$$s.t. x(k+1) = Ax(k) + Bu(k), \tag{2.2}$$

$$u \in \mathcal{U},$$

where $x(k) \in \mathbb{R}^n$ and $u(k) \in \mathbb{R}^m$, and A $\in \mathbb{R}^{n\times n}$, B $\in \mathbb{R}^{n\times m}$, are known matrices with constant entries of corresponding entries. The cost function $J(k)$ is linear quadratic, Linear Quadratic Predictive Control (LQPC), with symmetric weighting matrices Q and R, where $Q \geq 0$, $R > 0$, and $\mathcal{U}$ is an admissible control set.

$$\min_{u_0,\dots,u_{H_P-1}} = \sum_{k=0}^{H_P-1} x(k)^T Q x(k) + u(k)^T R u(k), \tag{2.3}$$

$$s.t.\, x(k+1) = Ax(k) + Bu(k), \qquad k = 0, \dots H_P - 1, \tag{2.4}$$

$$u(k) \in \mathcal{U}, \qquad x(k+1) \in \mathcal{X}, \qquad k = 0, \dots, H_P - 1,$$

$$x_0 = x(t) \equiv x(k).$$

The future states are described as,

$$\hat{X}(\mathrm{k}) = G\Delta U(k) + \Gamma x(k), \tag{2.5}$$

$$\hat{X}(k) = \begin{bmatrix} \hat{x}(k+1) \\ \vdots \\ \hat{x}(k+H_P) \end{bmatrix} = \underbrace{\begin{bmatrix} A \\ \vdots \\ A^{H_P} \end{bmatrix}}_{\Gamma} x(k) + \underbrace{\begin{bmatrix} B & \cdots & 0 \\ \vdots & \ddots & \vdots \\ A^{H_P-1}B & \cdots & B \end{bmatrix}}_{G} \underbrace{\begin{bmatrix} \Delta u(k) \\ \vdots \\ \Delta u(k+H_P-1) \end{bmatrix}}_{\Delta U}, \tag{2.6}$$

$$\hat{X}_0 = \Gamma \hat{x}(k). \tag{2.7}$$

For regulation proposes, and considering the general case which intent to lead the state to zero, the linear MPC without constraints solution of (2.3) is given by:

$$\Delta U^* = -K_c \hat{x}(k) = -(G^T Q G + R)^{-1} G^T Q \hat{X}_0 \tag{2.8}$$

and implementing the first element of the optimal prediction at each sampling instant *k* defines a receding horizon control law

$$u(k) = \Delta U^*(1). \tag{2.9}$$

Remark that if $\mathcal{U}$ and $\mathcal{X}$ are polyhedral (a finite intersection of half-space), this is a Quadratic Program, that can be can be solve fast, efficiently and reliably, using modern solver tools.

2.3.1 Linear Plant Model

For linear systems, the dependence of predictions $x(k)$ on $u(k)$ is linear. A quadratic minimization cost function as (2.3) is therefore a quadratic function of the input sequence vector $\boldsymbol{u}$. Thus $J(k)$ can be expressed as a function of $\boldsymbol{u}$ in the form,

$$J(k) = \boldsymbol{u}^T(k) H \boldsymbol{u}(k) + 2 f^T \boldsymbol{u}(k) + g, \tag{2.10}$$

where H is a constant positive definite (or possibly positive semi-definite) matrix, and f, g are respectively a vector and scalar which depend on $x(k)$. The online MPC optimization therefore comprises the minimization over $\boldsymbol{u}$ of a quadratic objective:

$$\min_{u} \; \boldsymbol{u}^T(k)H\boldsymbol{u}(k) + 2f^T\boldsymbol{u}(k). \tag{2.11}$$

In the absence of constraints, unconstrained MPC, the optimization $\mathbf{u}^*(k) = \min_{\mathbf{u}} J(k)$ has a closed-form solution which can be derived by considering the gradient of *J* with respect to **u**:

$$\nabla_u J = 2H\boldsymbol{u} + 2Fx(k). \tag{2.12}$$

Clearly $\nabla_{\mathrm{u}} J = 0$ must be satisfied at a minimum point of *J*, and since *H* is positive definite (or positive semidefinite), any $\boldsymbol{u}$ such that $\nabla_{\mathrm{u}} J = 0$ is necessarily a minimum point. Therefore the optimal $\boldsymbol{u}^*$ is unique only if *H* is non-singular and is then given by,

$$\boldsymbol{u}^*(k) = -H^{-1}Fx(k). \tag{2.13}$$

Remark that, sufficient conditions for *H* to be non-singular are for example that $R > 0$ or $Q, \bar{Q} > 0$ and the pair (A,B) is controllable.

If *H* is singular (i.e. positive semi-definite rather than positive definite), then the optimal $\mathbf{u}^*$ is non-unique, and a particular solution of $\nabla_{\mathrm{u}} J = 0$ has to be defined as,

$$u(k) = -H^{\dagger}Fx(k), \tag{2.14}$$

where $H^{\dagger}$ is a left inverse of *H* (so that $H^{\dagger}H = \mathrm{I}$).

Implementing the first element of the optimal prediction $\boldsymbol{u}^*(k)$ at each sampling instant *k* defines a receding horizon control law. Since *H* and *F* are constant, this is a linear time-invariant feedback controller $u(k) = K_C\, x(k)$, where the gain matrix K_C is the first row of $-H^{-1}F$ for the single-input case (or the first n_u rows for the case that *u* has dimension n_u), i.e.

$$u(k) = u^*(k|k) = K_C x(k), \tag{2.15}$$

$$K_C = -\begin{bmatrix} I_{n_u} & 0 & \dots & 0 \end{bmatrix} H^{-1}F. \tag{2.16}$$

Constrained MPC is used when structural limitations of the system to be controlled usually leads to control restrictions and avoiding such limitations may cause harmful effects as unstable cycle. However, for performance purpose, the control system should try to use the system as close to those limits as possible, without crossing them. Therefore, MPC uses a more direct approach by finding the optimal control in such a way that constraints are not violated.

Most typically, linear input and state constraints likewise imply linear constraints on $u(k)$ which can be expressed

$$A_c\boldsymbol{u}(k) \le b_c, \tag{2.17}$$

where A_c is a constant matrix and, depending on the form of the constraints, the vector b_c may be a function of $x(k)$. So, considering the optimization function (2.11) but now subject to linear constraints:

$$\min_{u} \ \boldsymbol{u}^T(k)H\boldsymbol{u}(k) + 2f^T\boldsymbol{u}(k), \tag{2.18}$$

$$s.t. \ A_c\boldsymbol{u}(k) \leq b_c. \tag{2.19}$$

This class of optimization problem is known as a quadratic programming (QP) problem, and given that H is a positive definite matrix and the constraints are linear, it is easy to show that (2.18) and (2.19) are a convex problem (i.e. both the objective (2.18) and constraints (2.19) are convex functions of the optimization variable $\mathbf{u}$. This kind of problem can be solved efficiently and reliably using commercial solver and specialized algorithms.

Generally, the constraints which are applied on control input, state or output assume the following form:

$$\underline{u} \leq u(k) \leq \overline{u}, \tag{2.20}$$

$$\underline{x} \leq x(k) \leq \overline{x}, \tag{2.21}$$

$$\underline{y} \leq y(k) \leq \overline{y}, \tag{2.22}$$

or even rate constraints:

$$\underline{\Delta u} \leq u(k) - u(k-1) \leq \overline{\Delta u}. \tag{2.23}$$

Input constraints commonly arise as a result of actuator limits, e.g. torque saturation in d.c. motors and flow saturation in valves and the state constraints may be active during transients, e.g. aircraft stall speed, or in steady-state operation as a result of e.g. economic constraints on process operation. In addition to the obvious equality constraints that the state and input should satisfy the model dynamics, inequality constraints on input and state variables are encountered in every control problem. While the equality constraints are usually handled implicitly (i.e. the plant model is used to write predicted state trajectories as functions of initial conditions and input trajectories), the inequality constraints are imposed as explicit constraints within the online optimization problem.

However, constraints are classified as *hard* or *soft*. The *hard* constraints, must always be satisfied, and when is not possible, the problem is becomes infeasible.

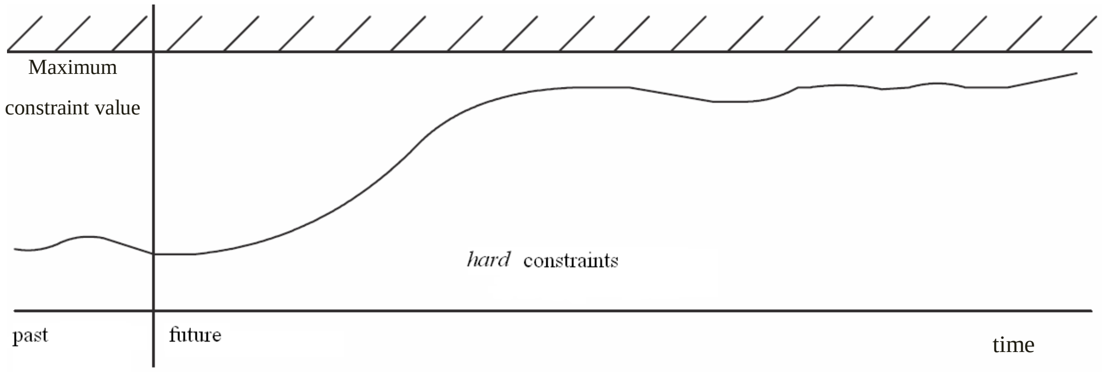

Figure 2.5. *Hard* constraint representation (Adapted from Froisy, 1994).

On the other hand, *soft* constraints may be violated if necessary to avoid infeasibility, generally with a penalization in the cost function.

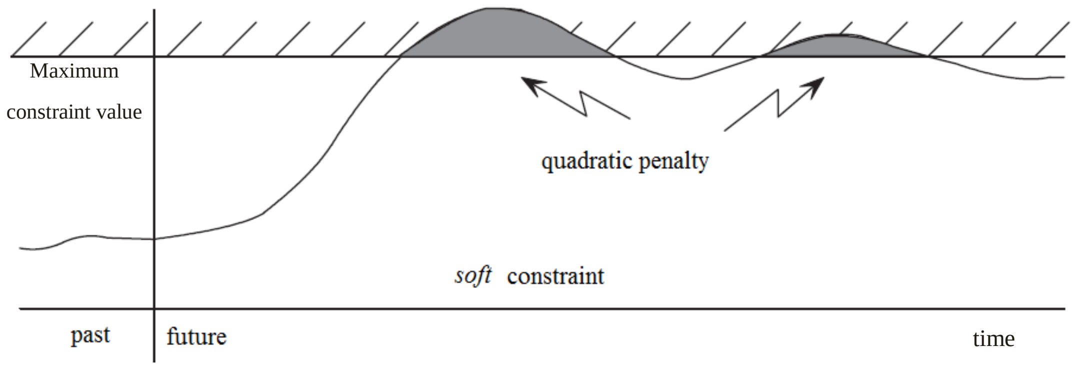

Figure 2.6. *Soft* constraint representation (Adapted from Froisy, 1994).

Chapter 4 shows an example of *hard* constraints application and in Chapter 6 and 7 *soft* constraints. Thus, constraints will be here generically described and exemplified.

To implement a *soft* constraint, allowing for example that the output variable exceeds the constraint value in a specified value $\epsilon \geq 0$,

$$y(t+j) \leq \overline{y} + \epsilon(t+j),$$

$$\epsilon(t+j) \geq 0, \;\; 1 \leq j \leq N_{soft}.$$

with N_{soft} representing the horizon where the *soft* constraint is considered.

Thus a new term is included in the cost function (2.18),

$$\min_{u} \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{v}^T \overline{\boldsymbol{H}} \boldsymbol{v} + \overline{\boldsymbol{b}}^T \boldsymbol{v}, \tag{2.24}$$

with

$$\boldsymbol{Hu} = -b, \tag{2.25}$$

$$\boldsymbol{v}^T = [\boldsymbol{u}^T \quad \epsilon^T], \overline{\boldsymbol{H}} = \begin{bmatrix} \boldsymbol{H} & 0 \\ 0 & \lambda_r \boldsymbol{I} \end{bmatrix},$$

$$\overline{\boldsymbol{b}}^T = [\boldsymbol{b}^T \quad 0], \epsilon = \begin{bmatrix} \epsilon(t+1) & \cdots & \epsilon(t+N_{soft}) \end{bmatrix}.$$

Where $\lambda_r > 0$ is the ponderation factor and $\overline{\mathbf{H}}$ the *Hessian* matrix. The optimization problem must also include,

$$y(t+j) - \epsilon(t+j) \leq \overline{y}, \epsilon \geq 0. \tag{2.26}$$

Now, to be able to be solved as a quadratic optimization problem the constraints must be expressed as inequalities constraints, assuming the following form:

$$\min_{u} \frac{\mathbf{1}}{\mathbf{2}} \boldsymbol{v}^T \overline{\boldsymbol{H}} \boldsymbol{v} + \overline{\boldsymbol{b}}^T \boldsymbol{v}, \tag{2.27}$$

$$s.t. A\boldsymbol{u} \leq c. \tag{2.28}$$

In a systematic way other *soft* constraints can be considered in the output value,

$$\underline{y}(t+j) - \epsilon(t+j) \leq y(t+j) \leq \overline{y}(t+j) + \epsilon(t+j), \qquad N_m \leq j \leq H_P, \tag{2.29}$$

And expressing the constraints as manipulated variables

$$\boldsymbol{Gu} - \epsilon \leq \mathbf{1}\overline{y}, \tag{2.30}$$

$$-\boldsymbol{Gu} - \epsilon \leq -\mathbf{1}\underline{y}, \epsilon \geq 0.$$

With **1** representing a (H_P-N_m) matrix with unitary values, and **G** the dynamic matrix and the incremental control vector.

To implement *hard* constraints on *U*, I

$$\underline{U} \leq u(t+j) \leq \overline{U}, \qquad N_m \leq j \leq H_{P.} \tag{2.31}$$

Expressing the constraints as manipulated variables,

$$\boldsymbol{Tu} \leq \mathbf{1}\overline{U} - 1u(t-1), \tag{2.32}$$

$$-\boldsymbol{Tu} \leq -\mathbf{1}\overline{U} + 1u(t-1).$$

Where $\boldsymbol{T}$ is an upper triangular matrix with ($N_C \times N_C$). Considering also *hard* constraints in *y*, the output is written as,

$$\underline{y}(t+j) \leq y(t+j) \leq \overline{y}(t+j), \qquad N_m \leq j \leq H_P, \tag{2.33}$$

and once again,

$$\begin{gathered} \boldsymbol{Gu} \leq \mathbf{1}\overline{y}, \\ -\boldsymbol{Gu} \leq -\mathbf{1}\underline{y}. \end{gathered} \tag{2.34}$$

Supposing a set of constraints acting over a process, where the control signal U amplitude, the actuator slew rate u and output signal y are limited. These constraints can be expressed as,

$$\begin{gathered} \underline{U} \leq u(t) \leq \overline{U} \quad \forall\, t, \\ \underline{u} \leq u(t) - u(t-1) \leq \overline{u} \ \forall\, t, \\ \underline{y} \leq y(t) \leq \overline{y} \ \forall\, t, \end{gathered} \tag{2.35}$$

Considering that the process has m inputs and n outputs with constraints acting along a horizon H_P, (2.35) can be reformulated

$$\begin{gathered} \mathbf{1}\underline{U} \leq \boldsymbol{Tu} + u(t-1) \leq \mathbf{1}\overline{U} \quad \forall\, t, \\ \mathbf{1}\underline{u} \leq \boldsymbol{u} \leq \mathbf{1}\overline{u} \ \forall\, t, \\ \mathbf{1}\underline{y} \leq \boldsymbol{Gu} \leq \mathbf{1}\overline{y} \ \forall\, t, \end{gathered} \tag{2.36}$$

where $\mathbf{1}$ is a matrix $(H_P \times n) \times m$ with $H_P m \times m$ identity matrices, and $\boldsymbol{T}$ is a lower triangular matrix where the non-null inputs are identity matrices with $(m \times m)$, and writing the constraints in a condensed form, results in,

$$A\boldsymbol{u} \leq c,$$

with,

$$\boldsymbol{A} = \begin{bmatrix} \boldsymbol{T} \\ -\boldsymbol{T} \\ \boldsymbol{I}_{H_P \times H_P} \\ -\boldsymbol{I}_{H_P \times H_P} \\ \boldsymbol{G} \\ -\boldsymbol{G} \end{bmatrix}; \qquad \boldsymbol{c} = \begin{bmatrix} \mathbf{1}\overline{U} - \mathbf{1}u(t-1) \\ -\mathbf{1}\underline{U} + \mathbf{1}u(t-1) \\ \mathbf{1}\overline{u} \\ -\mathbf{1}\underline{u} \\ \mathbf{1}\overline{U} \\ -\mathbf{1}\underline{U} \end{bmatrix}. \tag{2.37}$$

The QP solution can be obtained using a modified Lemke's method (Camacho, 1993; Igreja and Cruces, 2002).

2.3.2 **Nonlinear Plant Model**

Although the majority of processes are inherently nonlinear, most of the applications use linear dynamic models. Several reasons are behind this fact, or because empirical linear models can be easily identified because mostly process work nearby a desire operation point, or because linear models may present sufficient precision when in presence of high quality the feedback measures. Linear models may use quadratic objective functions that are simply solve with LQ convex programming which provide a solution that should converge to the optimal criterion.

The use of nonlinear models in MPC is motivated by the need to improve the control of processes with robust linearity's through by improving the prediction quality.

Thus, MPC has a large population of potential applications even for nonlinear systems, according to (Allgöwer et al., 2004), the key characteristics and properties of NMPC are:

- NMPC allows the direct use of nonlinear models for prediction;
- NMPC allows the explicit consideration of state and input constraints;
- In NMPC a specified time domain performance criteria is minimized on-line;
- In NMPC the predicted behaviour is in general different from the closed-loop behaviour;
- For the application of NMPC typically a real-time solution of an open-loop optimal control problem is necessary;
- To perform the prediction the system states must be measured or estimated;
- The optimization problem is nonconvex, more difficult to solve than QP;
- The computation time increases because the difficulty to find the solution of the optimisation problem;

If a nonlinear prediction model is employed, then due to the nonlinear dependence of the state predictions $\mathbf{x}(k)$ on $\mathbf{u}(k)$, the MPC optimization problem is significantly harder than for the linear model case. This is because the cost in equation (2.3), which can be written as $J(\mathbf{u}(k), x(k))$, and the constraints, $g(\mathbf{u}(k), x(k)) \leq 0$, are in general nonconvex functions of $\mathbf{u}$(k), so that the (2.3) optimization problem,

$$\min_{\boldsymbol{u}} J(\boldsymbol{u}; x(k)), \tag{2.38}$$

$$s.t.\ g(\boldsymbol{u}; x(k)), \tag{2.39}$$

becomes a nonconvex nonlinear programming (NLP) problem. As a result there will in general be no guarantee that a solver will converge to a global minimum of (2.38) and the times required to find even a local solution are typically orders of magnitude greater than for QP problems of similar size. Unlike QP solvers, the computational loads of solvers for nonlinear programming problems are strongly problem-dependent.

2.3.3 **Generalized Predictive Control**

Another similar MPC strategy that will be used in Chapter 4, is Generalized Predictive Control. (GPC). GPC was developed by (Clarke et al., 1987) and is a popular form of MPC. In the original version of GPC, stability was not guaranteed because of using finite horizon. New versions of GPC were based on the idea that the stability of GPC could be guaranteed if in the last part of the prediction horizon the future outputs are constrained at the desired set point, and also the prediction horizon is properly selected. The well-known example for this category is Stabilizing Input/Output Receding Horizon Control (SIORHC). The GPC controller uses a Controlled Auto-Regressive Integrated Moving Average (CARIMA) model as presented in the next difference equation,

$$A(q^{-1})\Delta y(t) = q^{-d}B(q^{-1})\Delta u(t) + C(q^{-1})\xi(t), \tag{2.40}$$

where $y(t)$ is the process output, $u(t)$ is the control variable, d is the delay, $\xi(t)$ is the measure noise (perturbations, model errors). The GPC control law is obtained with the minimization of the following equation,

$$J_{GPC} = \sum_{j=N_m}^{H_P} [y(t+j) - y_r(t+j)]^2 + \sum_{j=1}^{N_C} R\Delta u^2(t+j-1), \tag{2.41}$$

where R is the control weight, N_m is the minimum horizon, specifying the beginning of the horizon in the cost function from which point the output error is taken into account, and H_P represents the prediction horizon, specifying the last output error that is taken into account. N_C is the control horizon, $y(t+j)$ and $y_r(t+j)$ are the output and reference signal, $\Delta u(t+j-1)$ is the control signal increment at $(t+j-1)$. The control weight and control horizon are the main two tunings GPC parameters that allows obtaining different predictive controllers in order to adjust them to the desire control plant (Clarke et al., 1987). Remark that, the control action affects the process output only after the delay, it is reasonable to choose the minimum horizon higher or equal to the process delay. If the process delay is unknown then, the delay can be set to one and the minimum horizon to zero without the loss of stability. The choice of the minimum horizon can be interesting in case of non-minimum phase processes.

Consider the polynomial,

$$C(q^{-1}) = A(q^{-1})\Delta E_j(q^{-1}) + q^{-j}F_j(q^{-1}), \tag{2.42}$$

where,

$$E_j(q^{-1}) = 1 + e_1 q^{-1} + \ldots + e_{n_e} q^{-n_e},$$
$$F_j(q^{-1}) = f_0 + f_1 q^{-1} + \ldots + f_{n_f} q^{-n_f}, \tag{2.43}$$
$$n_e = j - 1;\ n_f = max(n_a, n_c - j),$$

are stablished knowing j and $A(q^{-1})$ e $C(q^{-1})$.

By manipulating the model equation (2.40) and (2.42), equation (2.46) can be obtained,

$$y(t+j) = \frac{F_j(q^{-1})}{C(q^{-1})} y(t) + \frac{G_j'(q^{-1})}{C(q^{-1})} \Delta u(t+j-d) + E_j(q^{-1})\xi(t+j), \tag{2.44}$$

with,

$$G_j'(q^{-1}) = E_j(q^{-1})B(q^{-1}). \tag{2.45}$$

The noise is uncorrelated from the measurable signals in instant t, so the output prediction can be written for $(t+j)$ as,

$$\hat{y}(t+j) = \frac{F_j(q^{-1})}{C(q^{-1})} y(t) + \frac{G_j'(q^{-1})}{C(q^{-1})} \Delta u(t+j-d), \tag{2.46}$$

with,

$$G_j'(q^{-1}) = C(q^{-1})G_j(q^{-1}) + q^{-j}\bar{G}_j(q^{-1}), \tag{2.47}$$

and substituting in (2.44),

$$\hat{y}(t+j) = \underbrace{\frac{F_j(q^{-1})}{C(q^{-1})} y(t) + \frac{\bar{G}_j(q^{-1})}{C(q^{-1})} \Delta u(t-d)}_{available\ information\ at\ \ t\ instant} + \underbrace{G_j(q^{-1})\Delta u(t+j-d).}_{future} \tag{2.48}$$

From (2.48) the effect of the past and future control actions, can be separated,

$$\hat{y}(t+j/t) = \frac{F_j(q^{-1})}{C(q^{-1})} y(t) + \frac{\bar{G}_j(q^{-1})}{C(q^{-1})} \Delta u(t-d) \tag{2.49}$$

Equation (2.46) can be represented in vectorial form,

$$\hat{Y} = G\Delta U + f \tag{2.50}$$

With **f** formed with the free responses,

$$f = \left[\hat{y}(t + \frac{N_m}{t}) \quad \hat{y}(t + N_m + \frac{1}{t} \quad \ldots \quad \hat{y}(t + \frac{H_P}{t})\right]^T, \tag{2.51}$$

and

$$\Delta\boldsymbol{U} = [\Delta u(t) \quad \Delta u(t+1) \quad \dots \quad \Delta u(t+N_C-1)]^T, \tag{2.52}$$

where,

$$\hat{Y} = [\hat{y}(t+N_m) \quad \hat{y}(t+N_m+1) \quad \dots \quad \hat{y}(t+H_P)]^T, \tag{2.53}$$

$$\mathrm{G} = \begin{bmatrix} g_{N_m-d} & \cdots & g_0 & 0 & 0 & \cdots & 0 \\ g_{N_m-d+1} & \cdots & g_1 & g_0 & 0 & \cdots & 0 \\ \vdots & \ddots & & & \ddots & & \vdots \\ \vdots & & \ddots & & & & g_0 \\ \vdots & \cdots & & & & & \vdots \\ g_{H_P-d} & g_{H_P-d-1} & \cdots & & & & g_{H_P-N_C-d+1} \end{bmatrix}, \tag{2.54}$$

with **G** $(H_P - N_m + 1)\times N_C$ dimension.

GPC cost function can also be presented in vectorial form,

$$J_{GPC} = [\hat{Y} - Y_r]^T[\hat{Y} - Y_r] + R\Delta U^T \Delta U, \tag{2.55}$$

where

$$Y_r = [y_r(t+N_m) \quad y_r(t+N_m+1) \quad \dots \quad y_r(t+H_P)]^T. \tag{2.56}$$

Thus, (2.55) is minimized obtaining the follow control law,

$$\Delta U = [G^T G + RI]^{-1} G^T [Y_r - f]. \tag{2.57}$$

Being GPC a receding horizon controller, only the first element of the calculated control signal sequence is to be applied on the process. The procedure of minimization of the cost function is repeated in the next sampling instant. The applied control signal is:

$$u(t) = u(t-1) + \Delta u(t). \tag{2.58}$$

So, GPC allows threating process with unknown or varying delays, constrained systems, nonlinearities, non-minimum phase processes as well open-loop unstable plants (Clarke et al., 1987b). The GPC control structure is presented in Figure 2.7.

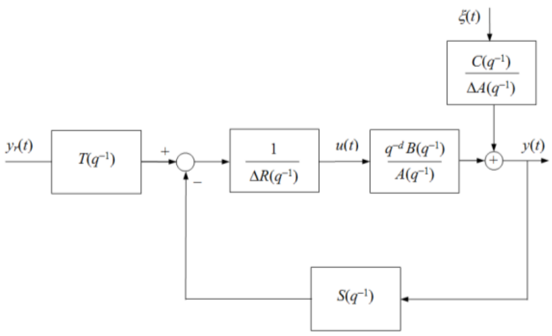

Figure 2.7. GPC control structure.

With M

$$M = [1 \quad 0 \quad \ldots \quad 0][(G^T G + \Lambda I)^{-1} G^T], \tag{2.59}$$

where $M = [m_{N_m} \quad m_{N_m+1} \quad \cdots \quad m_{H_P}]$.

So, the control applied to the process can be written as,

$$\Delta u(t) = M[Y_r - f]. \tag{2.60}$$

According Figure 2.7, the control law is given by,

$$R(q^{-1})\Delta u(t) = T(q^{-1}) y_r(t + H_P) - S(q^{-1}) y(t), \tag{2.61}$$

where

$$R(q^{-1}) = C(q^{-1}) + q^{-d} \sum_{j=N_m}^{H_P} m_j \bar{G}_j\,(q^{-1}), \tag{2.62}$$

$$S(q^{-1}) = \sum_{j=N_m}^{H_P} m_j\, F_j(q^{-1}), \tag{2.63}$$

$$T(q^{-1}) = C(q^{-1}) \sum_{j=N_m}^{H_P} m_{H_P+N_m-j}\, q^{-(j-N_m)}, \tag{2.64}$$

$n_r = H_P - N_m$; $n_s = max(n_a, n_c - H_P)$ and $n_t = max(n_c, n_b)$.

Substituting (2.61) in (2.40),

$$y(t) = \frac{[q^{-d} B(q^{-1}) T(q^{-1})] y_r(t + N_2)}{[A(q^{-1})\Delta R(q^{-1}) + q^{-d} B(q^{-1}) S(q^{-1})]} + \frac{C(q^{-1}) R(q^{-1}) \xi(t)}{[A(q^{-1})\Delta R(q^{-1}) + q^{-d} B(q^{-1}) S(q^{-1})]} \tag{2.65}$$

With (2.65), the closed loop characteristic polynomial is calculated by,

$$P_{mf}(q^{-1}) = A(q^{-1})\Delta R(q^{-1}) + q^{-d} B(q^{-1}) S(q^{-1}). \tag{2.66}$$

As mentioned, the first generation in the MPC family, such as DMC, IDCOM and GPC used a finite prediction horizon. This feature made it possible to incorporate constraints in the control strategy, a capability that is not supported by infinite horizon LQ control. Initially in GPC, because of using finite horizon, stability was not guaranteed in his original version. But later, this issue was overcome with the idea that the stability of GPC could be guaranteed if in the last part of the prediction horizon the future outputs are constrained at the desired set point and the prediction horizon is properly selected. So, the stability weaknesses of the first generation were overcome with the second generation with these two methods that are the most popular in this category, the SIORHC (Mosca et. al 1990), or Constrained Receding Horizon Predictive

Control (CRHPC) and Stable Generalised Predictive Control (SGPC). SIORCH optimize a quadratic function over a prediction horizon subject to the condition that the output matches the reference value over a further constraint range.

Another kind of adaptive predictive controller algorithm is Multistep Multivariable Adaptive Regulator, MUSMAR (Greco et al., 1984) is a data driven algorithm designed for the adaptive regulation of linear Autoregressive–Moving-Average Model with exogenous inputs model (ARMAX) plants. This algorithm combines several features, the optimization of a receding horizon quadratic cost, it assumes a constant feedback over the prediction horizon, the cost function is minimized based on predictive models for both plant input and output signals and the estimation of the predictors and the data are separate.

This algorithm possesses attractive local self-optimizing properties and was extendedly studied during the eighties and nineties years of the last century (Mosca at al., 1989; Rato et al., 1997) and successfully applied in recent years in many areas (Nunes, et al., 2007).

2.3.4 **Stability and Feasibility**

In this work, feedback stability is provided by choosing a sufficiently long predictive horizon and proven by results. Feasibility is achieved by the use of *soft* constraints (5.1) in the optimization problem formulation.

Table 2.1. Simulation parameters for the several prediction horizons

Parameter	**A_1**	**Units**
Ξ	1	
ψ	5000	
Φ	200	
φ	1	
R_{eq}	50	ºC/kW
C_{eq}	9.2×10^3	kJ/ºC

To exemplify, several predictive horizons were chosen to demonstrate the influence of this parameter. The simulation time was also counted to evaluate the system performance under the several H_P chosen, 1, 6, 12 and 24h. The simulations were made for one house in the same conditions used in Chapter 5, using optimization problem (5.1) and the dynamical model (3.1). The used parameters are described in Table 2.1 and the obtained results in Figure 2.9 to Figure 2.11. It is considered that the system knows the existence of load disturbances, Figure 2.8, inside the selected H_P. Simulations were made in an Intel Core 1.59GHz, 2,0GB of RAM machine.

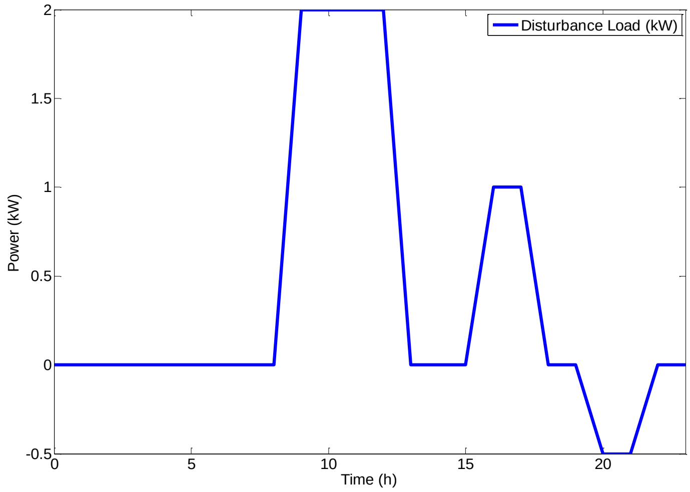

Figure 2.8. Disturbance load profile in the several prediction horizons.

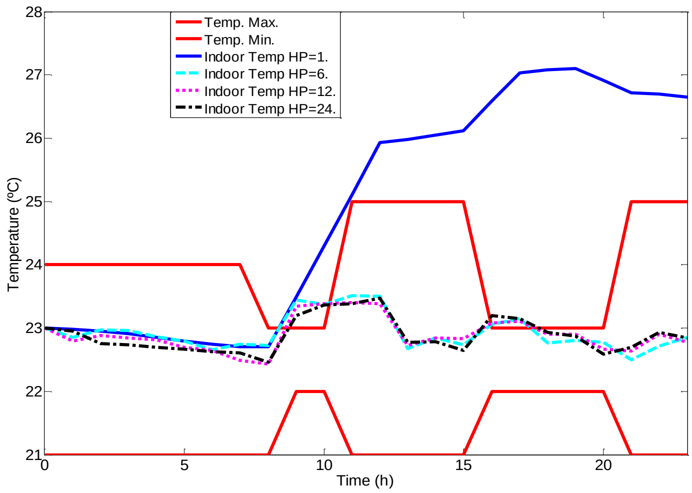

Figure 2.9. Indoor temperature profile for the several prediction horizons.

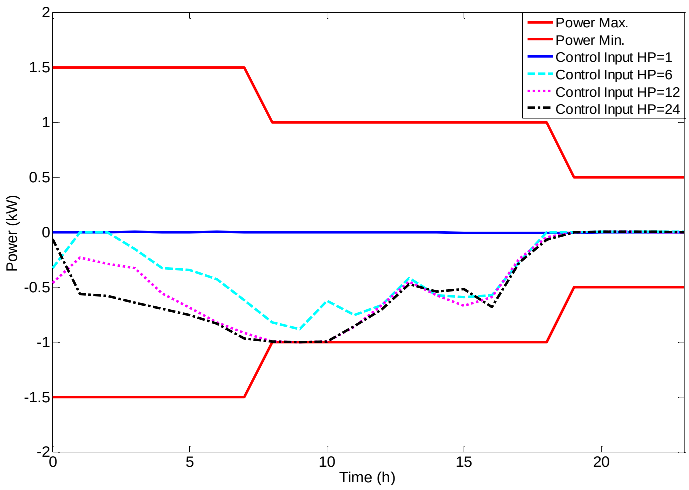

Figure 2.10. Power profile for the several prediction horizons.

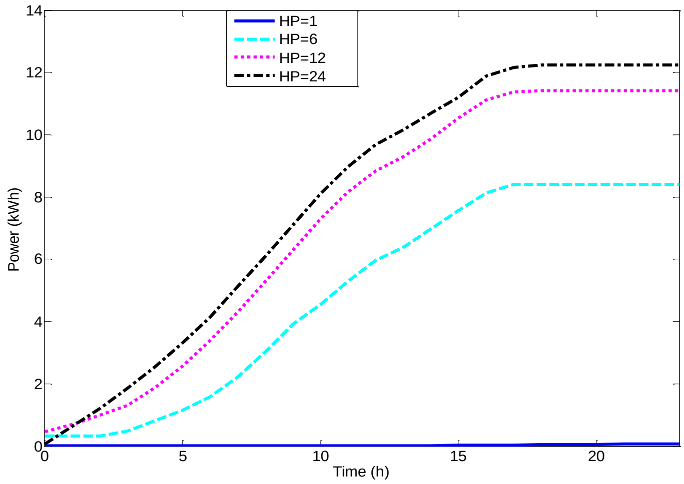

Figure 2.11. Consumption profile for several prediction horizons.

As can be seen in Figure 2.9, with H_P=1 the system becomes instable, the indoor temperature diverge from the chosen comfort zone because with this horizon the power consumption is almost null. The indoor temperature and power profiles are similar with the others H_P, but remark that, with H_P=24, the system is able to anticipate sooner all the disturbances and constraints and by that reason the power consumption is higher in order to also maintain the temperature inside bounds. It can be seen that the compromise between comfort and consumption is notorious, the controllers are always attempting to accomplish both constraints, but when is not possible, it compensates with one inside range and the other outside. The application of *soft* constraints allows this behaviour and the problem feasibility.

As expected, Table 2.2 shows that higher prediction horizons has the drawback of higher computational efforts, the compromise between anticipation, feasibility and computational efforts must be taken in account when the parameters are chosen.

Table 2.2. Computational efforts under several prediction horizons

H_P (h)	Computational effort (s)
1	2,8
6	4,4
12	52,5
24	289,5

2.3.5 **Centralized MPC**

The continuous instrumentation development associated to the need of improvements in processes and environmentally conscious solutions has made the process control become even more complex. With this, the implementation and maintenance of centralized MPC algorithms have become an important issue and often complicated to treat. Some of the major obstacles encountered in the use of advanced control techniques, such as MPC, are the difficulty of communication between sensors and processing units in geographically distributed systems and computational limitations for some optimization problems. Although, for large and geographically distributed systems, the two mostly used control strategies are centralized or decentralized. Centralized control can coordinate subsystems but may suffer from the curse of dimensionality and failures in the central control unit. In general, in most of the applications, MPC is implemented in a centralized scheme, where the complete system is modelled and all the control inputs are computed in one optimization problem, Figure 2.12.

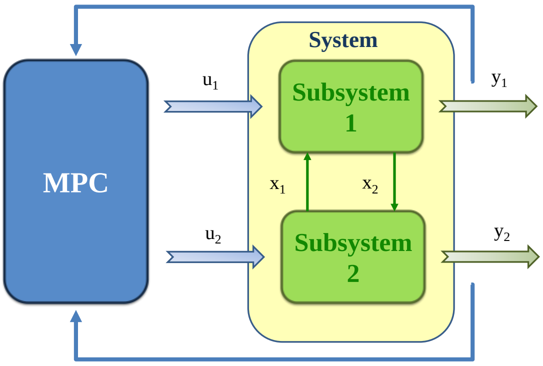

Figure 2.12. Centralized MPC architecture (Scattolini, 2009).

The overall system model can be represented as a discrete, linear time invariant (LTI) model with the form,

$$x(k+1) = Ax(k) + Bu(k), \tag{2.67}$$

$$y(k) = Cx(k)\,,$$

in which,

$$A = \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1Ns} \\ \vdots & \vdots & \ddots & \vdots \\ A_{i1} & A_{i2} & \dots & A_{iNs} \\ \vdots & \vdots & \ddots & \vdots \\ A_{Ns1} & A_{ns2} & \dots & A_{NsNs} \end{bmatrix}, B = \begin{bmatrix} B_{11} & B_{12} & \dots & B_{1Ns} \\ \vdots & \vdots & \ddots & \vdots \\ B_{i1} & B_{i2} & \dots & B_{iNs} \\ \vdots & \vdots & \ddots & \vdots \\ B_{Ns1} & B_{Ns2} & \dots & B_{NsNs} \end{bmatrix},$$

$$C = \begin{bmatrix} C_{11} & 0 & \dots & 0 \\ 0 & C_{22} & \ddots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & C_{NsNs} \end{bmatrix}, \tag{2.68}$$

$$u = [u'_1 \quad \dots \quad u'_{Ns}]' \in \mathbb{R}^m,$$

$$x = [x'_1 \quad \dots \quad x'_{Ns}]' \in \mathbb{R}^n, \tag{2.69}$$

$$y = [y'_1 \quad \dots \quad y'_{Ns}]' \in \mathbb{R}^z.$$

For each subsystem i= 1, 2,…, Ns, the (u_i, x_i,, y_i) represents the subsystem input, state and output vector respectively. Thus, in the centralized MPC framework, the following optimization problem is solved,

$$\min_{x,u} J(\boldsymbol{x}, \boldsymbol{u}; x(k)) = \sum_i w_i J_i(\boldsymbol{x}_i, \boldsymbol{u}_i; x_i(k)), \tag{2.70}$$

$$s.t. \qquad x(k+1) = Ax(k) + Bu(k), \tag{2.71}$$

$$u_i(k) \in \mathcal{U}_i \qquad i = 1, \dots, N_S,$$

$$J_i = \sum_{j=1}^{N} L_i \left(x_i(k+j), u_i(k+j-1)\right),$$

$$L_i = \frac{1}{2}\left[x_i^T Q_i x_i + u_i^T R_i u_i\right].$$

Where $w_i > 0, \sum w_i = 1$, $Q_i \geq 0$, $R_i > 0$ and $\left(A_i, \sqrt{Q_i}\right)$ detectable and $x_i(k)$ given.

For any system, centralized MPC achieves the best attainable performance (Pareto optimal) as the effect of interconnections among subsystems are accounted for exactly. Additionally, existent conflicts among controller objectives are solved optimally (Venkat et al., 2008).

Normally, centralized MPC can be used in the form of a supervisory controller that have access to all variables in the network and that determines actions for all actuators. Due to practical and computational issues the implementing a centralized controller may not be feasible. Individual hubs may not want to give access to their sensors and actuators to a centralized authority and even if they would allow a centralized authority to take over control of their hubs, this centralized authority could have computational problems with respect to required time when solving the resulting centralized control problem. This approach is ideal for small scale systems, but when the control and optimization problem involves a large scale system the conventional approach requires the decomposition of the global system into smaller subsystems.

2.3.6 **Decentralized MPC**

Alternatively, decentralized control uses a distributed approach that decomposes a large optimization problem in small ones that can be solve by agents, preserving or even improving the final performance (Camponogara et al., 2002). Each agent solves its sub-problem and computes its own control actions, taking in to account possible mutual influences between other neighbouring agents. Thus, decentralized control is desirable for being scalable and robust but fails to account for the mutual influence among neighbouring sub- systems that can have long-range effects. The key feature of a decentralized control framework is that there is no communication between the different local controllers. While there are some important reviews on decentralized control see (Christofides et al., 2013) for a tutorial review. A schematic for decentralized MPC architecture, with two subsystems with state coupling, is shown in Figure 2.13.

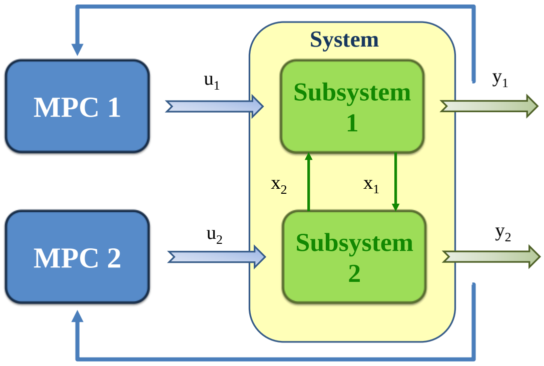

Figure 2.13. Decentralized MPC architecture (Scattolini, 2009).

Note that strong interactions between different subsystems may prevent one from achieving stability and desired performance with decentralized control. So, in order to achieve closed-loop stability as well as performance in the development of decentralized MPC algorithms, the interconnections between different subsystems are assumed to be weak or negligible, and are considered as disturbances which can be compensated through feedback so they are not involved in the controller formulation explicitly. Thus, the effect of external subsystems on the local subsystem is omitted in this modelling framework. Remark that, when the above assumption is not valid it may lead to a reduced control performance. Assuming a block diagonal structure for the overall dynamic system, each subsystem is modelled by

$$x_i(k+1) = A_{ii}x_i(k) + B_{ii}u_i(k), \tag{2.72}$$

$$y_i(k) = C_{ii}x_i(k) \qquad i = 0, \dots, N_S.$$

In the decentralized MPC framework, each subsystem MPC solves the following optimization problem,

$$\min_{x,u} J_i(\boldsymbol{x}_i, \boldsymbol{u}_i; x_i(k)), \tag{2.73}$$

$$s.t.\ \ x_i(l+1|k) = A_{ii}x_i(l|k) + B_{ii}u_i(l|k), \qquad k \le l, \tag{2.74}$$

$$u_i \in \mathcal{U}_i, \qquad k \le l.$$

Each decentralized MPC solves an optimization problem to minimize its local cost function.

2.3.7 **Distributed Model Predictive Control**

The MPC have also evolved as a distributed systems control methodology (Negenborn, et al., 2006; Scattolini, 2009; Igreja et al., 2012). Distributed or decentralised Model Predictive Control allows the distribution of decision-making while handling constraints in a systematic way. DMPC algorithms, offers the same features of MPC but have the advantage of supporting the distribution of sensing and control using local controllers/agents that cooperate by exchanging information to decide their control actions. This is the reason why it was the chosen method to deal with this kind of system. These DMPC infrastructures are suitable to use in a MAS (see Chapter 2.4) framework where, in a distributed environment, several agents employing individually a MPC control strategy are able to interact and receive influence from neighbour subsystems, exchange predictions on their future state and incorporate this information into their local MPC problems.

Large scale interconnected systems, such as power systems, water distribution, traffic systems, etc, require control techniques adjusted to the distributed nature of the system, as, decentralized or distributed control (Krogh, 2001). However, in decentralized MPC approach, the information exchange between subsystems is ignored and each subsystem is constructed with its individual control system forming a traditional centralized control scheme. This decentralized control architecture may result in poor system-wide control performance if the subsystems interact significantly (Venkat, et al., 2006). In distributed MPC, there is not a single MPC controller but instead there are multiple MPC controllers, each for a particular system. Typically, there is dynamical interaction among the systems that the individual controllers consider. Each of the controllers adopts the MPC strategy as outlined above for controlling its system but now not only considering dynamics, constraints, objectives, and disturbances of the subsystem under consideration but also considers the interactions among the systems. Each local controller solves an MPC problem based on local information and may hereby share information with the other controllers to improve the overall performance.

Figure 2.14 represent a simple distributed control system where it is assume that local regulators interact between them, obtaining by this way some information on the behaviour of the others. This information is normally related with future predicted control or state variables computed locally, so that any local regulator can predict the interaction effects over the considered prediction horizon.

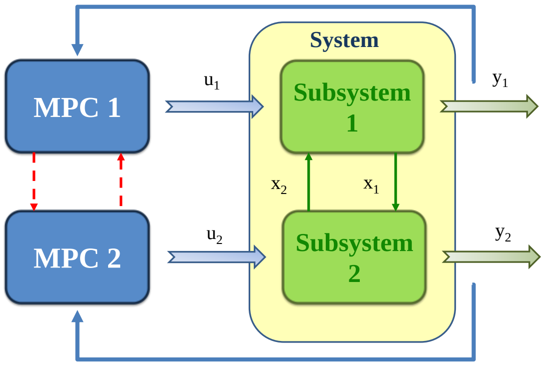

Figure 2.14. Distributed MPC architecture (Scattolini, 2009).

The generalized optimal state-input trajectory for $(\boldsymbol{x}_i^p, \boldsymbol{u}_i^p)$ for subsystem i (i=1,2,…N_s) at iteration p is obtained as the solution to the optimization problem,

$$\min_{\boldsymbol{x}_i, \boldsymbol{u}_i} J_i\big(\boldsymbol{x}_i, \boldsymbol{u}_i; x_i(k)\big), \tag{2.75}$$

$$s.t.\ x_i(l+1|k) = A_{ii}x_i(l|k) + B_{ii}u_i(l|k) + \sum_{j\neq i}\big[A_{ij}x_j^{p-1}(l|k) + B_{ij}u_j^{p-1}(l|k)\big], \qquad k \leq l \tag{2.76}$$

$$u_i \in \mathcal{U}_i, \qquad k \leq l, \qquad i = 0, \dots, N_S.$$

When moving from a centralized MPC to a distributed MPC setting, several key concepts become relevant. In a distributed MPC setting, a system or subsystem refers to the entity being controlled by the controller. The overall system is the combination of all systems or subsystems under control merged into one large-scale system. The notions of global versus local distinguish between the overall system and the system or subsystem under control by a particular controller. Hence, frequently appearing concepts are local objectives, local dynamics, local constraints, and local disturbances. The terms interconnecting and shared are often used in combination with the terms variables and constraints to denote explicitly those components that represent the connections or couplings between different systems. In a distributed setting, a particular controller has neighbours, or neighbouring controllers. The neighbours are those controllers that control systems that are coupled or influence the system under control by this particular controller. Communication takes places among the controllers, which can exchange information, for example, regarding local states, local objectives, and/or local constraints. Information can then be taken into account by the controllers to implement a coordination or negotiation process. The controllers can be structured in control layers or levels, leading to a hierarchical control structure. Here, typically at higher levels, controllers consider slower time scales and larger systems in a more abstract way, whereas at lower levels, controllers consider faster time scales and smaller systems in a more detailed way. The potential of distributed MPC lies in the unique combination of the strengths of MPC (namely, feedback with feed-forward control in a receding horizon fashion, multi-objective optimization, and explicitly handling of constraints) with the negotiation and coordination possibilities provided by communication. The role played by communication in this context is essential. For example, the distinction between decentralized and distributed MPC lies in whether or not the controllers actively communicate with one another to determine actions. In decentralized control architecture, there is no direct communication between controllers; controllers take into account the influence of neighbouring systems only by responding to the dynamics of the systems they are controlling. This constraint typically limits the performance that the decentralized MPC control scheme can achieve. In fact, in a decentralized MPC scheme, controllers may be opposing one another's actions, even though they may not have the intention to do so. In a distributed MPC setting, such a situation can be prevented because the controllers can communicate about what actions they are going to take when and obtain agreement on an optimal timing.

In summary, DMPC is an evolving technology that advocates the distribution of sensing and control while preserving the same features of standard MPC, namely, the use of a prediction model and the explicit handling of constraints (Saluje et al., 2011).

As mentioned DMPC strategies can be characterized by the type of couplings or interactions assumed between constituent subsystems (Trodden & Richards 2010), (Keviczky, et al., 2006).

For example, dynamically coupled systems can be seen in several contributions (Doan, et al., 2009; Camponogara et al. 2002; Ling, et al., 2005; Dunbar 2007; Giovanini, et al., 2007; Venkat, et al., 2008, Alessio, et al., 2011).

Another common application of DMPC is on subsystems where the states are not dynamically coupled but are coupled in their objective functions. A DMPC coupling via the cost function (Wang, et al., 2010), considers the DMPC of systems with interacting subsystems having decoupled dynamics and constraints but coupled costs. Works with similar approaches can be seen in literature (Raffard, et al., 2004; Franco, et al. 2007).

Other different strategy involves subsystems sharing coupled constraints and many approaches have been presented in the literature. In Riggs, et al., 2010 is establish an algorithm where an optimization problem is performed by different subsystems with their own objective functions and local constraints, but share a common coupled constraint which limits the behaviour of the independent systems.

Biegel, et al.,(2014) presents a dual decomposition as a means to coordinate a number of subsystems coupled by state and input constraints where each subsystem have a model predictive controller while, a centralized entity manages the subsystems via prices associated with the coupling constraints. This system allows coordination of all the subsystems without the need of sharing local dynamics, objectives and constraints.

Another approach (Müller, et al., 2012) presents a framework for DMPC of discrete-time nonlinear systems with decoupled dynamics, but subject to coupled constraints and a common, cooperative task. Each system exchange information about is predicted trajectories with its neighbours in order to be able to achieve the common objective and to satisfy the coupling constraints. Systems coupled by constraints can be seen in (Waslander, et al., 2004; Keviczky, et al., 2006; Richards & How 2007; Kuwata et al., 2007).

Due to its features, DMPC (Camponogara, et al., 2002) has been developed for application to large-scale systems, namely as process control (Borrelli, et al., 2005), chemical plants (Venkat, et al., 2004) and or teams of vehicles (Riggs, et al., 2010) (Kuwata, et al., 2007), in which control by a single centralised agent would require excessive communication, computation and reliance on a single processor.

Due the characteristics mentioned above DMPC, are been applied in many distributed applications, and several approaches and architectures to this control scheme are emerging.

Some studies are applying MPC to reduce and optimize the energy consumption in the residential sector, namely, to deal with temperature set points regulations (Morosan, et al., 2010; Bălan, et al., 2009; Freire, et al., 2008). In particular Freire, et al., (2008), with a DMPC control algorithm based a modified version of Benders' decomposition the control problem objective is to minimize the heating energy bills while maintaining a certain indoor thermal comfort.

A DMPC scheme with stability constraint (DMPC-SC), where controllers to obtain coordination with each other, spread information about their predictions and their local state measurements and use them in their local computations, is described in (Krogh, 2001).

For serially connected processes, (Zhang & Li, 2007), proposed a networked MPC scheme with neighbourhood optimization where each MPC unit receives information about the foreseeable action for its neighbour sub-processes. Therefore, the exchange information allows cooperation between subsystems and the optimizer to generate a suitable control decision for each sub-process.

Bendtsen et al., (2010), proposed hierarchical approach, consisting of a three-level structure with a high level MPC controller, a second level of so-called aggregators, controlled by an online MPC-like algorithm, and a lower level of autonomous units. The approach is motivated by smart-grid electric power production and consumption systems, being the goal to accommodate load variations on the grid, arising from varying consumption and natural variations in power production, e.g. from wind turbines.

Stewart et al., (2010) also proposed a hierchical cooperative distributed MPC without requiring additional coordinating controllers. The head of each subsystem performs a small additional calculation at each pack of information exchange to reduce the volume of communication and to hide input trajectories between neighbours.

Negenborn, (2007), develop a multi-agent MPC control structure with applications to control problems in power networks. The control agent uses the prediction model to predict the behaviour of the system under various manners, and establish the actions that optimize the behaviour of the system and minimize the costs existing in the objective function.

Ventak (2006), proposed, a cooperative distributed MPC framework, where the objective functions of the local MPCs are modified to achieve global control objectives.

Besides the advantages above mentioned, DMPC seems to be the right approach to deal with complex distributed systems, they can take into account all available information and that it can therefore anticipate undesirable situations in the future at an early stage.

As mentioned, for the control problem of large-scale systems, centralized model predictive control is impractical due to a number of limitations, including the computational efforts and limited communication, and due this fact, more research is needed in distributed and hierarchical model predictive control methods in order to develop new methods and algorithms to implement in large-scale systems. Smart grids are characterized by complex dynamics and mutual influences between all the involved identities and the algorithms should be able to deal with couplings in the dynamics and the constraints between subsystems, and guarantee feasibility and stability of the closed-loop system.

Instead, DMPC distributes control decision-making among agents corresponding to the different subsystems making up the whole. The challenge is then how to coordinate efforts to ensure that the distributed decisions lead to constraint satisfaction, feasibility and stability of the overall closed-loop system. Several strategies for DMPC have been presented in the literature, and many theoretical results exist, including those for feasibility and stability; see Scattolini (2009) for a comprehensive survey. The approaches are broadly divisible by the type of couplings or interactions assumed between constituent subsystems. The degree of coupling among the subsystems varies. In the most complex situation, the dynamics or/and constraints of subsystems are coupled. The method presented assumes the latter type of coupling, and has agents update their plans one at a time, with iteration, to ensure coupled constraint satisfaction; however, unlike other methods, it also permits a flexible order of updating.

Robustness to disturbances is a key challenge in the development of MPC (Mayne et al., 2000), and is harder still when control decision-making is decentralised; few DMPC schemes in the literature offer robustness. In Richards and How (2007), robust feasibility and stability are guaranteed by updating each subsystem's plan in a sequence, subject to tightened constraints, and while 'freezing' the plans of others. Alternative approaches include treatment of interconnected subsystems' state trajectories as bounded uncertainties, and using min-max optimization (Jia & Krogh 2002) – though the complexity issues with such an optimisation method are well documented (Mayne et al., 2000). Using the comparison model approach to robustness (Fukushima & Bitmead 2005), another distributed method (Kim & Sugie 2005) uses worst-case predictions of state errors, determined based on a robust control Lyapunov function, and tightens constraints accordingly. Magni & Scattolini (2006) propose a robust stable decentralised algorithm for non-linear dynamically coupled systems, with no information exchange between agents, although for an asymptotically decaying disturbance.

The new algorithm in this thesis exploits this feature to achieve flexibility in communication. An additional advantage of this approach is that the optimisation involves only the nominal system dynamics, avoiding the large increase in computational complexity associated with the inclusion of uncertainty in the optimisation as mentioned in (Scokaert & Mayne 1998). Many distributed methods proposed in the literature (e.g. Du et al., (2001), (Kim & Sugie 2005), (Dunbar & Murray 2006), (Alessio & Bemporad 2007), (Richards & How 2007), (Venkat et al., 2008) do not consider the implications that the scheduling of local optimisations has on the time required for communications. For example, the constraint-tightening DMPC approach proposed by (Richards & How, 2007), also for dynamically decoupled systems with coupled constraints, assumes repeated instantaneous exchanges during each sampling period.

2.4 Multi-Agents systems (MAS)

There are several ways to define an agent. Despite all the definitions, the most common view describes agents like been a high-level software abstraction, which efficiently describes a complex software entity, or, intelligent entities with three main characteristics:

- Pro-Activeness (they react to external events and they are driven to their objectives);
- Social ability (they can cooperate or compete between them);
- Autonomy (they can decide in order to archive their objectives);
- Multi-agent systems can be seen as a group of distributed, autonomous and intelligent agents within an environment, where they can act and react in order to work together to achieve a global goal.

Large interconnected networks can hardly be controlled in a traditional way due to its distributed characteristics and considerable control capabilities over the network operation. Multi-agent systems have characteristics that meet these requirements, they are able to model complex systems introducing the possibility of agents having common or conflicting goals. They may decide cooperating for mutual benefit or may compete to serve their own interests (Xu et al., 2010). Thus, from the single agent concept to the group of agent's concept, MAS are a powerful means to represent systems in a natural way. A system is traditionally defined as a group of components interacting together to achieve an overall objective or a number of objectives known as the system level objective(s). Each component in a system can be seen as an agent if it possesses the characteristic of agency, i.e. if it performs computations and its action is being feedback into the environment (Abbass et al., 2011). Distributed infrastructures are interconnected and maintain communication between each other is suitable for MAS technology (Raza et al., 2005) due the follow characteristics:

- Agents assess situation on the basis of measurements from sensing devices or that received from other entities;
- Agents cast their influence on performance of networks via commands to actuators and other identities;
- The agents differ in complexity from trivial threshold detectors that merely decide based upon a single measurement to highly intelligent systems;
- Agents have to make real time decisions from local, rather than global state information;
- Agents including controllers for individual devices are designed with simple decision rules based upon response thresholds that are expected to give most appropriate responses to a collection of situations generated.

Smart grids can be seen as an environment where a set of simple entities called agents can play the role of source, load, or any other component integrated in the environment. With the agents interaction, some collective intelligent can be achieved, they cooperate or compete in other to reach their objective.

MAS architectures have also others advantages, they are not dependent on a particular technology, with proper messaging tools, different programming languages can be used and interact together (Roche et al., 2010), and, due the agents autonomy, they can leave or enter in the environment without any perturbation.

2.4.1 **MAS architectures**

Researchers are still attempting to categorize the different types of MAS and agents within MAS. They are trying to identify characteristics and features that an agent must possess and also by defining categories of agents and MAS. In (Ferber, 1999) is presented a number of categorizations of MAS and one of the most accepted formal definitions of as: MAS= {*E, O, A, R, Or, Op*} where:

- *E* is the environment, a space in which objects (including objects *O* and agents *A*) are located;
- *O* is a set of objects in the environment other than the agents;
- *A* is the set of agents in the environment;
- *R* is an assembly of relations;
- *Or* is an assembly of operators; and,
- *Op* is an assembly of operations.

Due to the flexibility of MAS, several control architectures can be also found in order to respond to the variety of power systems, such as, voltage control, microgrid management, distributed network control and restoration, to manage and obtain the desire degree of intelligence. However, some general types of control structures can be identified and they are commonly encountered in theory and practice, *single-agent*, *multi-agent single-layer* and *multi-layer*. A *single-agent* control structure,

Figure 2.15 occurs when it is assumed that there is only one control agent that has access to all actuators and sensors of the network and thus directly controls the physical network. This control structure is referred to as an ideal, since in principle such a control structure can determine actions that give optimal performance.

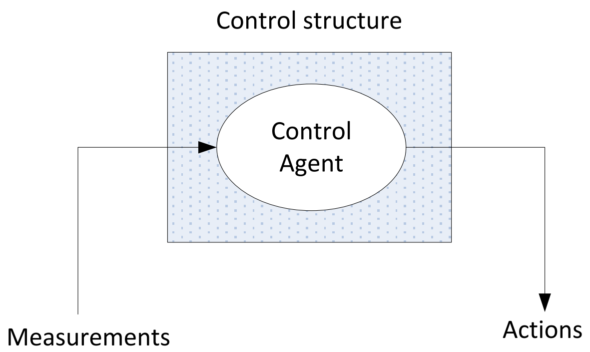

Figure 2.15. Single-agent control structure. (Adapted from Negenborn 2007).

When there are multiple control agents, each of them considering only its own part of the network and being able to access only sensors and actuators in that particular part of the network, then the control structure is referred to as a multi-agent single-layer control structure,

Figure 2.16. If in addition the agents in the control structure do not communicate with each other, the control structure is decentralized. If the agents do communicate with each other (dot line), the control structure is distributed.

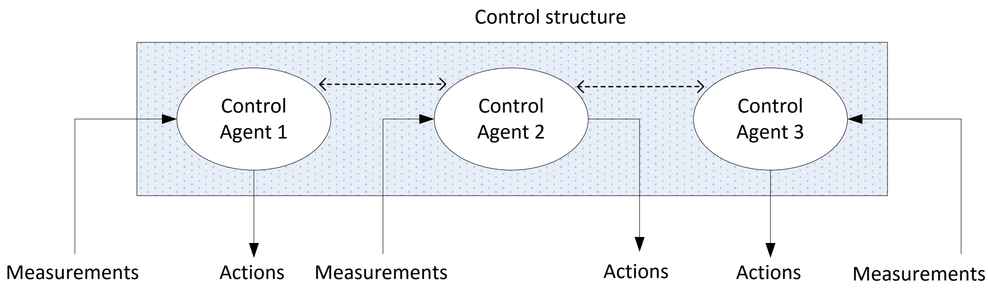

Figure 2.16. Multi-agent single layer control structure. (Adapted from Negenborn 2007).

A *multi-layer* control structure can be defined when there are multiple control agents and some of these control agents have authority over other control agents, in the sense that they can force or direct other control agents,

Figure 2.17. A multi-layer control structure typically is present when one control agent determines set-points to a group of other control agents working in a decentralized or distributed way. Due to the authority relationship between agents or groups of agents, this structure can also be referred to as a supervisory control structure, or a hierarchical control structure.

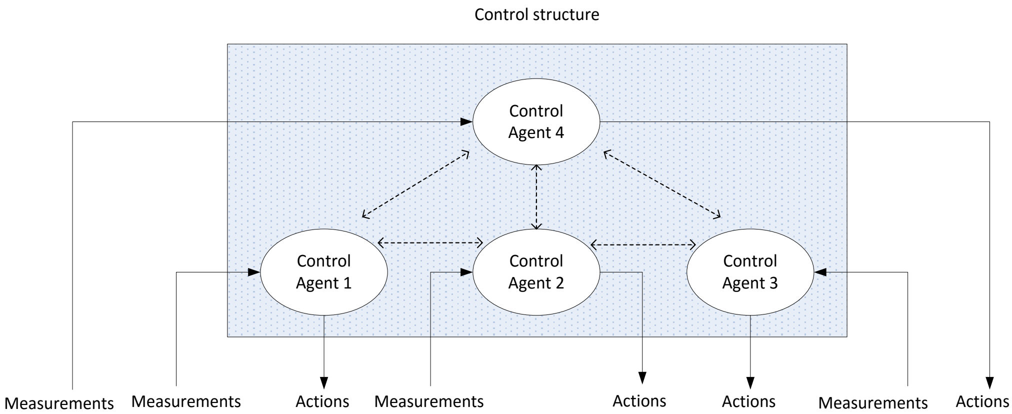

Figure 2.17. Multi-layer control structure. (Adapted from Negenborn 2007).

Single-agent control structures in general, have the advantage of deliver the best performance possible, and that they have been studied extensively in the literature, in particular for small-scale systems. Although, in large scale systems, there are several issues related with, robustness, reliability, scalability, responsiveness and communication delays that complicate the use of this structure.

Multi-agent control structures can deal or at least reduce these issues, but typically, they have a lower performance comparatively with single-agent.

Decentralized *multi-agent single-layer* control structures have the advantage, over the distributed, of lower computational requirements and faster control, because the inexistence of communication between the controllers. However, this advantage will typically be at the price of decreased overall performance. The advantage of a distributed multi-agent single layer control structure is therefore that improved performance can be obtained, although at the price of increased computation time due to cooperation, communication, and perhaps negotiation among control agents. The multi-agent multi-layer control structure, despite of been more complex, provides the possibility to obtain a trade-off between system performance and computational complexity (Negenborn 2007).

Although all the existing diversity, to respond to the several challenges mentioned above, most of the authors use a hierarchical layered structure (Zeng et al., 2009; Dimeas et al., 2005; Li et al., 2010; Aung et al., 2008) to archive different objectives.

With the joint goal of achieving cost and energy savings Ab et al., (1996), shows how decentralized power load management at the customer side, automatically carried out by a ‘society’ of intelligent household, industrial and utility equipment, can be modelled in terms of independent hierarchical decentralized intelligent agents that communicate and negotiate in a computational market economy.

Lu & Chen (2009) proposes new a system-level scheme, a three layered MAS architecture, where the bottom layer is called physical layer, in which each agent correspond to one energy source (RE or traditionally), the middle layer is named application layer, which is composed of coordinator agent, fault diagnosis agent, and recover agent etc., which provides service to the physical layer. The top layer is the user interface layer, which enables the interaction between human and MAS.

Also with a hierarchical layered structure, the MAS main target present by Jian et al., (2009), is to maximize the efficiency of renewable energy resources.

Pipattanasomporn et al., (2009), describes the design and implementation of the multi-agent system for use in a microgrid. The proposed multi-agent system consists of a control agent, a DER agent and a user agent in multi-layer distributed architecture where all agents interact between them. The proposed design also includes a database agent that is responsible for storing system information, as well as recording the messages and data shared among agents.

In order to negotiate available energy quantities and needs on behalf of consumers and producer groups, Wedde et al., (2006 and 2008) developed a multi-level bottom-up solution with autonomous software agents.

Negenborn, (2007), develop a multi-agent control structure with applications to control problems in power networks, and compare the obtained results with the single-agent approach.

As showed, to respond to the several issues related with distributed nature of the future smart grids, the MAS structure demonstrate to be the best solution. The existent MAS designs mostly use layered and subsystems models were a group of agents is controlled by a superior control agent. However, large distributed systems may have innumerable identities, and due the necessary communication between agents, it is needed a high computational effort. Besides this fact, the increase of agents also increases the possibility of internal and external conflicts, leading to a possible performance reduction.

In order to solve these problems, it is necessary to develop new algorithms, control system designs, and MAS architectures that can provide the benefits of cooperation, communication and negotiation among control agents to increase the performance, but with lowest computational efforts, and also to reduce the complexities to obtain an optimal operation in a large-scale distributed environment.

Chapter 3

Dynamical Models and Scenarios Description

3.1 Introduction

The energy consumption optimization in future SGs will be based on grid-integrated near-real-time communications between various grid elements in generation, transmission, distribution and loads.

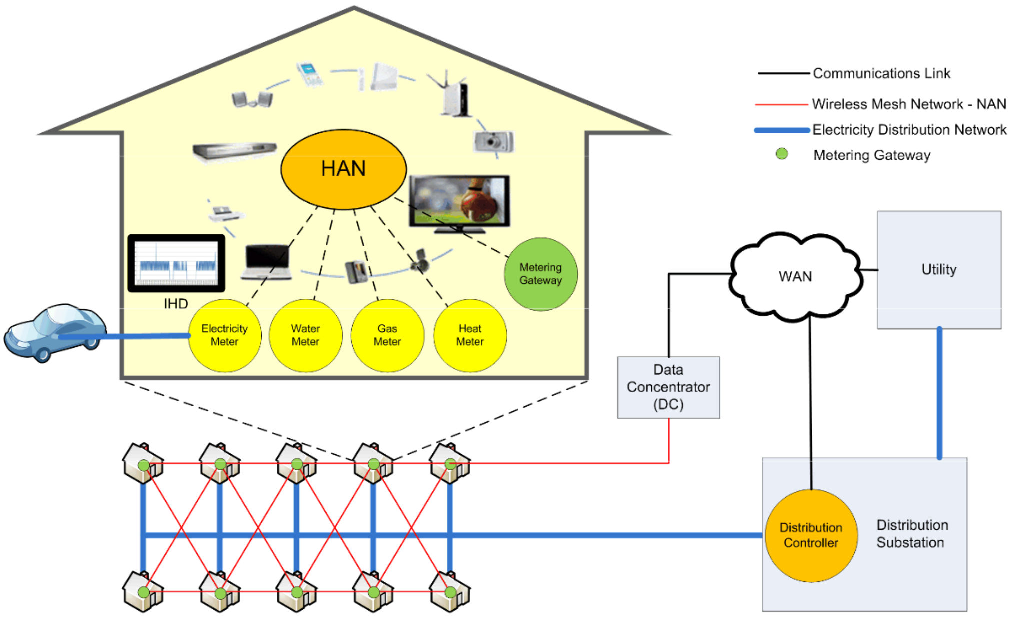

Figure 3.1. Typical smart grid architecture.

Figure 3.1 shows a typical smart metering architecture that is being reflected in the European standards development process (Fan et al., 2013).

Smart Grid is a concept for transforming the electric power grid using advanced automatic control and communications techniques and other forms of information technology. It integrates innovative tools and technologies from generation, transmission and distribution all the way to consumer appliances and equipment. This concept integrates energy infrastructure, processes, devices, information and markets into a coordinated and collaborative process that allows energy to be generated, distributed and consumed more effectively and efficiently. Costumers will have the chance to decrease their electricity bills by changing consumption from higher-priced hours to lower priced hours and smart metering will produce a market for new SG costumer products.

Thus, the scenario here described intends to be a realistic solution to take advantage of these SG's features.

3.2 Scenarios overview

A SG generally involves the application of smart meters, sometimes called advanced metering infrastructure (AMI), which usually include control and monitoring devices and appliances. Smart metering technology will be at the foundation of any SG design (Cecati et al., 2010). The most viable communication's technologies for the AMI are wireless and power line communication (PLC). SG's communication's infrastructure will also provide IP/Ethernet connectivity between most components, guiding the communication's interfaces and products towards TCP/IP-based networks. Power distribution companies are mostly interested in PLC because it represents the most cost effective solution and does not require additional investment in the communication's infrastructure. For these communication's requirements, companies like Siemens are offering customized communications network solutions for optic fibre, power line, and wireless infrastructures based on the accepted standards of the energy industry, Figure 3.2.

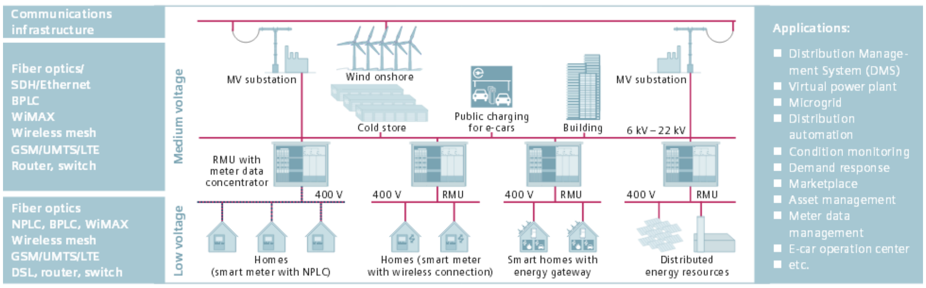

Figure 3.2. Typical energy distribution communication architecture for smart grids (Adapted from Siemens, 2014).

Because renewable energies are nowadays significantly expanded, electricity is being fed into both the medium- voltage and low-voltage grids, depending on changing external conditions (e.g., weather, time of day, etc.). These fluctuating energy resources can severely impair the stability of the distribution grid. One of the key challenges of a smart grid is therefore to quick balance out the energy supply and energy consumption in the distribution grid.

Thus, the scenario here presented has in consideration this challenge, intend to provide a solution to it based on, and taking advantage of all the AMI and communication technologies that SG provide.

The conceptual scenario involves a set of buildings with an electricity source provided by their own renewable energy park and energy storage as presented in Figure 3.3. Henceforward, the term house will be applied to classify any type of structure for habitation (houses), office buildings or other kind of analogous constructions. The set $W = \{w_1, w_2, \dots, w_{N_S}\}$ defines the Thermal Control Areas TCA's/house and the different spaces are described by $D_h = \{d_{\mathrm{h}1}, d_{\mathrm{h}2}, \dots, d_{hNd}\}$ and $\mathrm{h} = 1, \dots N_S$.

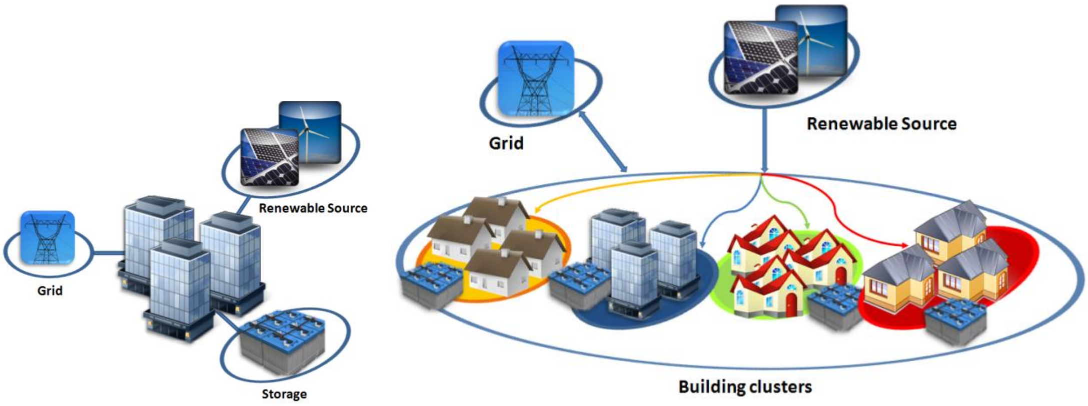

Figure 3.3. Implemented scheme.

Due the existing division diversity in houses, each area may vary in: construction materials, sun exposure, occupancy, indoor temperature set-points. This variety involves many different energy needs to weatherize the spaces, and for this a TCA is considered. Figure 3.4 presents a conceptual TCA smart thermostat which can be used as an interface for DSM. In the left side of the display the user is able to choose between three operating modes related with the control features. At the centre the user is able to program the division's comfort range and the particular time periods. On the right the cost, the *green* and *red* consumption are shown, allowing the user to access more specific other menus.

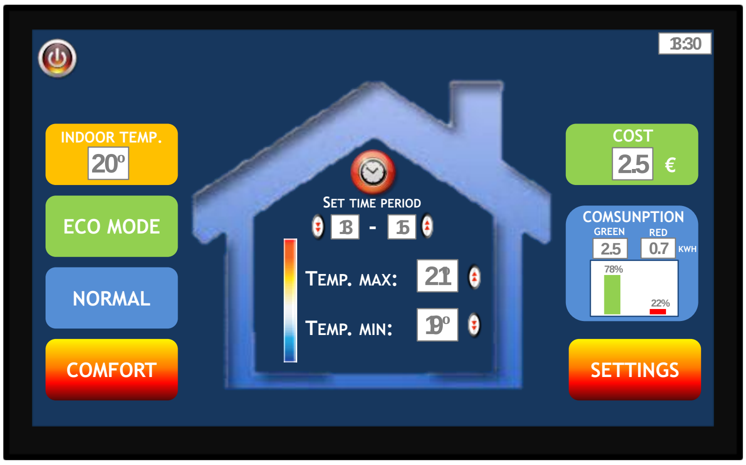

Figure 3.4. Thermal Control Area (TCA) smart thermostat controller vision.

Each division may have different thermal loads, thermal characteristics, occupancy and comfort temperature bounds and consequent different energy needs for heating/cooling the spaces, for this a Thermal Control Area (TCA) is considered. As mentioned, one TCA represents an autonomous thermal control entity within an environment where the actions and reactions are made in order to achieve a common goal. Therefore, as Figure 3.5 shows, depending from the desired infrastructure intent to be implemented, a set of buildings or a simple division may represent a TCA.

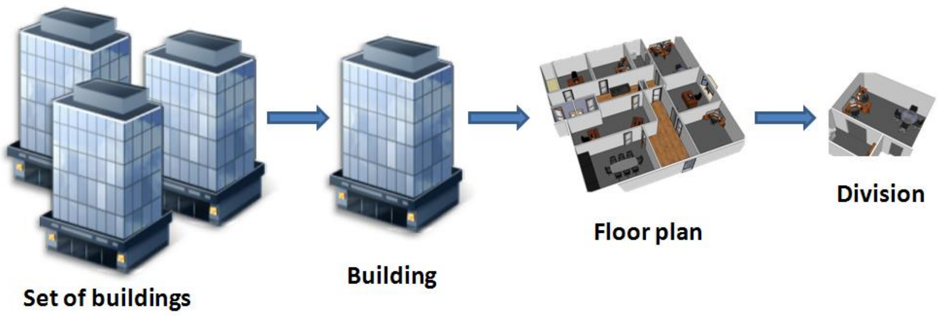

Figure 3.5. Thermal Control Area concept.

The idea is to use a MPC control law to adjust the indoor temperature set-point in each TCA. Taking advantage of the MPC characteristics, the system receives information on the outdoor's temperature forecasts, the future occupation, the indoor temperature frame and the thermal disturbances profile. The control action is conditioned by two constraints; thermal comfort and available energy. Using a DSM approach, the trade-off between the energy price and comfort limitations are system assured. The scenario considers the existence of two resources, the *red*, from the grid provided by fossil source and the *green*, from renewable or clean source. The first is always available with a kWh price always higher than the *green*. On the contrary the *green* is limited, intermittent and must be consumed, stored or grid delivered. Remark that if the clean source becomes insufficient the fossil is consumed increasing the energy costs.

So, the scenario considers that the traded electricity comes from a wholesale market which is priced in real time, where the market operators (MO) provide the *green* resource auction and the agents/TCA set a day-ahead their bids. The agents (one by each TCA) must bid in an auction, the price that they are willing to pay to consume the *green* resource. The bid value establishes a sequential order by which the TCA's can access to *green* energy. After consuming, each TCA sends to the next the information about how much of clean resource is still available. As mentioned, when the *green* resource becomes insufficient to satisfy all the demand, the *red* is available. The *red* resource consumption implies a penalty in the final cost function (5.1) due to the soft constraint violation imposed by the maximum available *green* resource. Notice that the divisions that interact thermally pass to each other information about future temperatures.

Each TCA receives several external inputs; the outdoor temperature, available renewable power forecasts, the MO kWh price, access order to the renewable resource and, when applied, the neighbour's indoor temperature forecasts. Figure 3.6 presents an example of the implemented TCA framework..

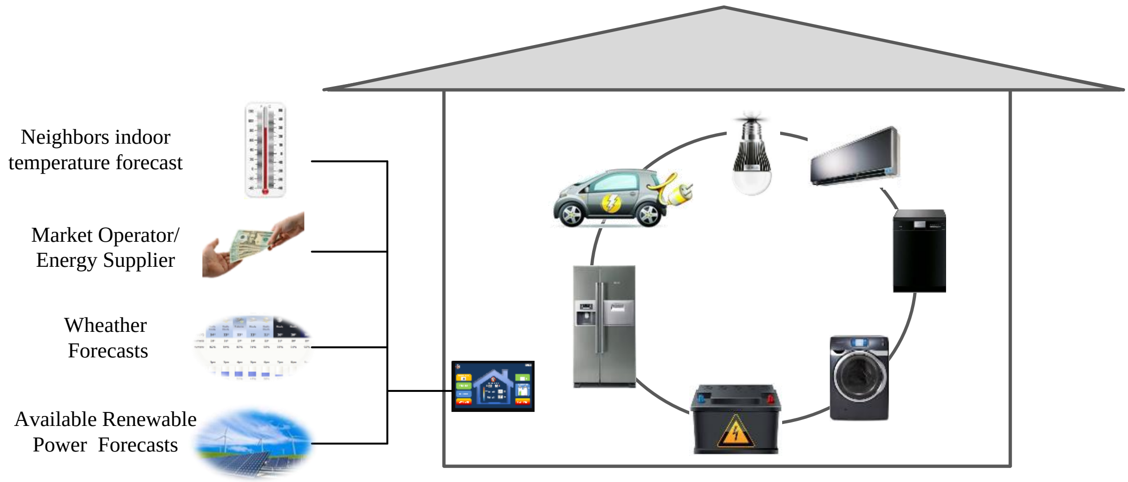

Figure 3.6. Example of a TCA conceptual framework.

The example depicted in Figure 3.6 shows the implemented system dependent from weather and power forecasts. Being wind and solar power not dispatched the production levels need to be predictable. Lower prediction errors help to balance the supply of wind energy with other sources, avoid consequences for incorrect estimation, as well as reducing the risk of having to buy energy from elsewhere. For wind power, the 24 hours ahead prediction average absolute error can be between 10–20% of installed capacity for one single zone. When aggregation of zones is made, the value may drop to 5-8% (VTT Technology 95, 2014; NREL, 2014). This can be partly due to the different accuracy for different types of sites, like different orography and roughness and how homogenous the grid cell for the numerical weather prediction model is. Prediction errors in low wind situations can still be higher relative to yearly energy. The forecast error is significantly lowered for the first six hours. The physical reason behind this is that wind itself has an auto-correlated nature and the model takes this into account by last measured power value when making forecasts into the future. As the forecast horizon increases the variation range seems to increase quite linearly.

The forecasting of solar energy production faces issues similar to those of wind. However, solar forecasting has significant predictability because the sun’s path through the sky is known. Accurate outdoor temperature forecasts are particularly valuable for electric or gas utilities. Nowadays, temperature forecasts are particularly reliable and accurate, with more than 92% accuracy with one day ahead (ForecastWacth, 2014).

Thus, in a scenario that privileges the renewable energy usage, the used demand side management approach allows the management of distributed loads, aiming the adjustment of the demand to the supply, providing thermal comfort, lower energy costs and lowering CO_2.emissons. By using this active DSM control, the optimal control strategies for various appliances can be generated whilst maximum utilisation of energy supplied from intermittent systems is guaranteed. The used DSM strategy is described in Chapter 3.3.

3.3 Demand side management approach

It is widely accepted that some form of real-time pricing arrangements is required to efficiently allocate DSM resources and fully inform users about the value of electricity at each point in time and location. Combination of ICT and business processes will be significant tools in the real time management of active networks, customers and commercial systems. Deregulated markets will let consumers to exploit information to move between competing energy suppliers based on energy cost, greenhouse gas emissions and social goals. A SG vision for the market has been developed in recent years through the work of a consortium of utilities. One option is an “eBay for electricity”, where continual electronic sales match energy consumers with energy producers. Soon customers will be able to bond the electricity pricing into their energy management system. High gap in price differentials between cost periods could result in greater shifts of energy usage. This needs to be accompanied by the application of intelligent appliances that would facilitate the implementation of DSM. In order to simplify such trading of energy among a very large number of smaller domestic participants, an electronic energy market system, supported for example by the internet, would need to be developed (an extension of power-exchange-type markets).

Thus, the developed system intends to provide a solution to be implemented in these future energy markets. It considers that the MO offers a *green* resource auction where each TCA sets a day-ahead their bids. The agents (one by each TCA) must bid in an auction, the price that they are willing to pay to consume the *green* resource according to their own consumption forecasts.

Utilities are able to see what power loads are creating bigger demand on their side, allowing them to more effectively implement DR programs for heating and cooling. Although, before demand–response systems can be effectively deployed on a wide scale in the residential sector, a number of technical challenges need to be resolved (infrastructure of communications, metering infrastructure, demand–response thermostats, etc.). This is likely to include some form of house energy management system that may rely on wireless technology that would automatically respond to price signals while taking into consideration the homeowner's preferences for cost versus comfort. Furthermore, the thermostat can be programmed to change settings with seasons. The thermostats can also have a notification feature to alert residents for calls for action, as well as an override feature, in case the customer chooses not to participate in the particular event. The customer main obtain information on buy-back rates via internet connections and takes appropriate action to manage peak loads. A key issue in these programmes is how sophisticated or complex they need to be to make the price signals. There is also the issue of verification to confirm that some benefit was obtained when the thermostat and air-conditioning system responded. Thermostats can also be pre-programmed to receive weather forecasts, to optimize both a consumer's energy savings and grid performance. The system uses weather forecasts and, when applied, neighbours indoor temperature forecasts, to anticipate major changes in the surrounding temperature and manage heating and cooling needs in advance, in the most energy-efficient way.

3.4 TCA Dynamical Models

The dynamics of temperature evolution in a building is one of the most important aspects of the overall building dynamics. The complexity in the dynamics of temperature evolution comes from the thermal interaction among rooms (and the outside). This interaction can either be through conduction across the walls, or through convective air exchanging among rooms. Consumption of energy is predominantly determined from a selection of materials and architectural solutions. It can be further reduced with efficient management of heating or cooling.

The building geometry constitutes the basic input for energy simulation. It is crucial to understand the differences between a building model created by an architect and a building model needed for energy simulation. For example, energy simulations spaces need to be defined by space boundaries, which are not necessarily the same as walls in an architectural model.

Thermal building simulation engines like, EnergyPlus or DOE-2 (Maile et al., 2007), predict the energy performance of a given building and thermal comfort for its occupants. In general, they support the understanding of how a given building operates according to certain criteria and enable comparisons of different design alternatives. This kind of software allows designing and characterizing in detail all the major features of a building architecture. Most of them also require a set of inputs which mainly consist in building geometry, internal loads, HVAC systems and components, weather data, operating strategies and schedules and simulation of specific parameters. However, these tools are only used for thermal simulation with predicted scenarios and previously established data, not working with real time inputs and data, which allow instant action over devices with control and decision mechanisms.

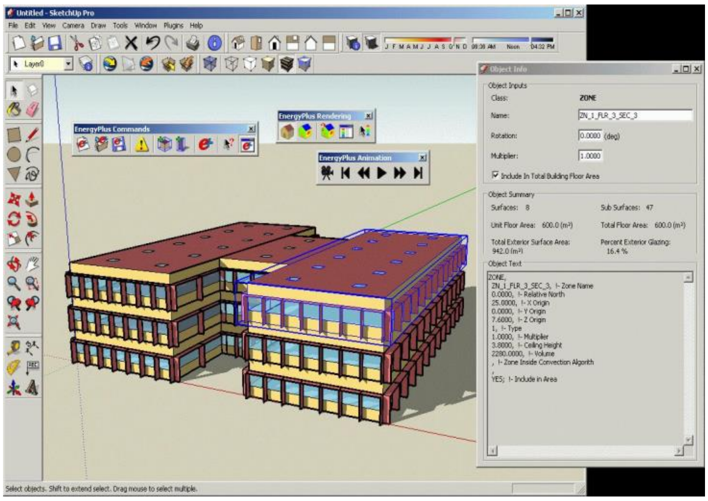

Figure 3.7. Energy modelling and building design process example with EnergyPlus.

Every energy simulation is based on thermodynamic equations, principles and assumptions. Since thermal processes in buildings are today complex and not totally understood, energy simulation programs estimate their predictions with qualified equations and methods. Therefore, results can be arbitrarily incorrect, if certain assumptions are not satisfied or matched in the simulation in real life. While two or three dimensional heat transfer would increase the accuracy of simulation results, geometry input and simulation running at real time is likely to become more complex. As mentioned earlier, the input, especially weather data and internal loads, for energy simulation is already based on assumptions, as are the thermodynamic concepts. For that matter, any simulation is based on assumptions; therefore complex interrelations can be simplified and managed. Users need to be aware of these assumptions and be able to decide whether they are reasonable for their specific simulation or not. Thus, the idea here presented is to apply the principle of analogy between two different physical domains that can be described by the same mathematical equations. Consequently, a linear electrical circuit represents the building, the state-space equations are obtained by solving the circuit. Here, the temperature is equivalent to voltage and the heat flux to current. Heat transmission resistance is represented by electrical resistance and thermal capacity by electrical capacity. The building equivalent circuit is obtained by assembling models of the walls, windows, internal mass, etc. For single-zone buildings, interior walls are part of the internal thermal mass, while exterior walls form the building envelope. Several approaches are seen in (Zong et al., 2012; Hazyuk et al. 2011) where is shown that building models can be simple or more complex depending on the objective.

Therefore, the first order energy balance model (3.1)-(3.3) that describes the dominant dynamics of a generic division, is considered suitable for control purposes (Barata et al., 2014b). Note that these are basic equations for edifice thermal modelling which can be described by several divisions and floors thermally interacting between them. For complete thermal models see (Hazyuk et al. 2011).

$$\frac{dT_l^i}{dt} = \frac{1}{C_{l_{eq}}^i}\left(Q_{l\,heat}^i - Q_{l_{losses}}^i + Q_{l_{Pd}}^i\right), \tag{3.1}$$

$$Q_{l_{losses}}^i = \frac{T_{out} - T_l^i}{R_{l_{eq}}^i} + \sum_{\substack{g=1 \\ (g \neq l)}}^{Nd_i} \frac{T_g^i - T_l^i}{R_{lg_{eq}}^i C_{l_{eq}}^i}\Delta t + \sum_{\substack{h=1 \\ (h \neq i)}}^{Ns} \sum_{m=1}^{Nd_h} \frac{T_m^h - T_l^i}{R_{lm_{eq}}^{ih} C_{l_{eq}}^i}, \tag{3.2}$$

$$R_{l_{eq}}^i = R_{l_{roof}}^i // R_{l_{windows}}^i // R_{l_{walls}}^i // R_{l_{th}}^i, \tag{3.3}$$

$$R_{l_{windows}}^i = \sum R_{window_{materials}}, \tag{3.3a}$$

$$R_{l_{roof}}^i = \sum R_{roof_{materials}}, \tag{3.3b}$$

$$R_{l_{walls}}^i = \sum R_{wall_{materials}}, \tag{3.3c}$$

where in (3.1), $Q_{l_{losses}}^i$ is heat and cooling losses (kW) from division (l), T_l^i the inside temperature (ºC), $C_{l_{eq}}^i$ the equivalent thermal capacitance (kJ/ºC), and $Q_{l\,heat}^i$ the heat and cooling power (kW) and $Q_{l_{Pd}}^i$ the external thermal disturbances (kW) (e.g. load generated by occupants, direct sunlight, electrical devices or doors and windows aperture to recycle the indoor air). In (3.2) T_{out} is the outdoor temperature (ºC), $R^{i}_{lg_{eq}}$ the thermal resistance between division (l) and the adjacent zone (g), $R^{i}_{l_{eq}}$ the equivalent thermal resistance (C/kW), and $R^{i}_{l_{th}}$ the air thermal resistance to bulk of division.

Figure 3.8 and Figure 3.9 present a simplified schematic representation of thermal-electrical modular analogy described by (3.1)-(3.3). $T^{i}_{1} \dots T^{i}_{Nd_i}$ are the inside temperature of adjacent spaces inside the same house, and $R^{i}_{1} \dots R^{i}_{Nd_i}$ the equivalent thermal resistance between the division and that adjacent areas.

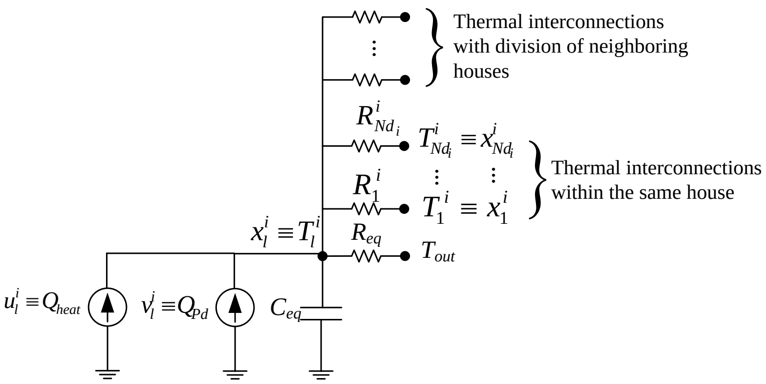

Figure 3.8. Schematic representation of thermal-electrical modular analogy for one division.

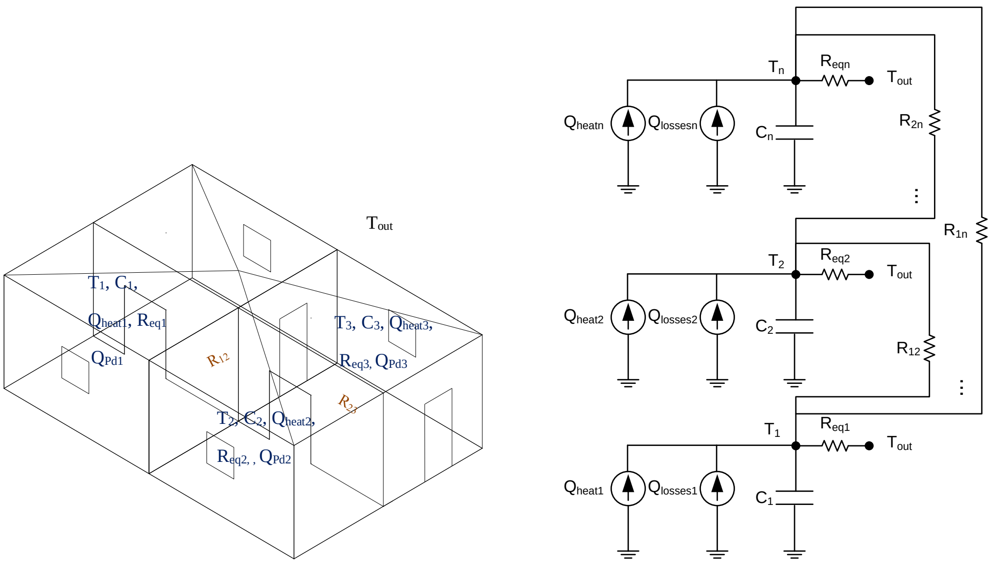

Figure 3.9. Generic schematic representation of thermal-electrical modular analogy for several divisions (Barata et al., 2014b).

As described in (Barata, et al., 2013b), a first order energy balance model is used to define the dominant dynamics of a generic division. Remark that these are the basic equations for structure thermal modelling and can be described by several divisions and floors interacting between them. In literature there are several degrees of complexity for house modelling techniques (Thavlov, 2008). The model used is linear and considers control purposes suitability,

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{v}(k), \tag{3.4}$$

where $\mathbf{x} \in \mathbb{R}^n$ is the state variable, indoor temperatures, vector containing all the divisions temperatures (ºC), $\mathbf{u} \in \mathbb{R}^m$ is the input vector containing all the heating and cooling power sources (W) to weatherize each division, and $\mathbf{v} \in \mathbb{R}^n$ includes all the disturbances (W), including load generated by occupants, solar radiation, any other heat/cooling sources or doors and windows aperture to recycle the indoor air, k is an integer number that denotes discrete time and $\mathbf{A} \in \mathbb{R}^{n\times n}$, $\mathbf{B} \in \mathbb{R}^{n\times m}$, are matrices.

Generically, using Euler discretization (Bequette, 2003) with a sampling time of Δ, the discrete model space-state representation of (3.4) can be written, for the N_s TCAs and for each division (l) as,

$$T_l^i(k+1) = A_{ll}^{ii} T_l^i(k) + B_l^i u_l^i(k) + \underbrace{\sum_{\substack{g=1 \\ (g\neq l)}}^{Nd_i} \left(A_{lg}^{ii} T_g^i(k)\right)}_{\substack{thermal\ contributions \\ from\ adjacent\ areas \\ inside\ the\ same\ house}} + \underbrace{\sum_{\substack{h=1 \\ (h\neq i)}}^{Ns} \sum_{m=1}^{Nd_h} \left(A_{lm}^{ih} T_m^h(k)\right)}_{\substack{thermal\ contributions \\ from\ adjacent\ areas \\ from\ other\ houses}} + v_l^i(k), \tag{3.5}$$

where

$$A_{ll}^{ii} = \left(1 - \frac{\Delta t}{R_{l_{eq}}^i C_{l_{eq}}^i}\right), B_l^i = \frac{\Delta t}{C_{l_{eq}}^i}, D_l^i = \sum_{\substack{g=1 \\ (g\neq l)}}^{Nd_i} \frac{T_g^i - T_l^i}{R_{lg_{eq}}^i C_{l_{eq}}^i}\Delta t + \sum_{\substack{h=1 \\ (h\neq i)}}^{Ns} \sum_{m=1}^{Nd_h} \frac{T_m^h - T_l^i}{R_{lm_{eq}}^i C_{l_{eq}}^i}\Delta t,$$
$$v_l^i = \frac{P_{l_{Pd}}^i \Delta t}{C_{l_{eq}}^i} + \frac{T_{oa}\Delta t}{R_{l_{eq}}^i C_{l_{eq}}^i}. \tag{3.6}$$

where Ns is number of TCA's, Nd_i is number of divisions inside subsystem (i), x_l^i is the indoor temperature in TCA/subsystem (i) inside division (l), u_l^i is the used power to provide comfort in TCA/subsystem (i) inside division (l), A_{lm}^{ih} is an element from the state matrix A that relates the state (indoor temperature) in division (m) from TCA/subsystem (h), with the state from division (l) in TCA (i) and v_l^i is the thermal disturbance in TCA/subsystem (i) inside division (l) e(g. load generated by occupants, direct sunlight, electrical devices or doors and windows aperture to recycle the indoor air), and T_{oa}, the temperature of outside air (ºC). Remark that the number of states variables in general model (3.4) is

$$n = \sum_{i=1}^{Ns} Nd_i.$$

To exemplify, Figure 3.10 illustrates a house/TCA with six divisions that thermally interact between them.

Figure 3.10. TCA divisions interaction simplified scheme;

So, for each division, (3.4) can be written as:

$$\begin{aligned}
x_1^1(k+1) &= A_{11}^{11}x_1^1(k) + A_{12}^{11}x_2^1(k) + B_1^1u_1^1(k) + v_1^1(k),\\
x_2^1(k+1) &= A_{22}^{11}x_2^1(k) + A_{21}^{11}x_1^1(k) + A_{23}^{11}x_3^1(k) + A_{24}^{11}x_4^1(k) + A_{26}^{11}x_6^1(k) + B_2^1u_2^1(k) + v_2^1(k),\\
x_3^1(k+1) &= A_{33}^{11}x_3^1(k) + A_{32}^{11}x_2^1(k) + A_{35}^{11}x_5^1(k) + A_{36}^{11}x_6^1(k) + B_3^1u_3^1(k) + v_3^1(k),\\
x_4^1(k+1) &= A_{44}^{11}x_4^1(k) + A_{42}^{11}x_2^1(k) + A_{45}^{11}x_5^1(k) + A_{46}^{11}x_6^1(k) + B_4^1u_4^1(k) + v_4^1(k),\\
x_5^1(k+1) &= A_{55}^{11}x_5^1(k) + A_{53}^{11}x_3^1(k) + A_{54}^{11}x_4^1(k) + A_{56}^{11}x_6^1(k) + B_5^1u_5^1(k) + v_5^1(k),\\
x_6^1(k+1) &= A_{66}^{11}x_6^1(k) + A_{62}^{11}x_2^1(k) + A_{63}^{11}x_3^1(k) + A_{64}^{11}x_4^1(k) + A_{65}^{11}x_5^1(k) + B_6^1u_6^1(k) + v_6^1(k),
\end{aligned} \tag{3.7}$$

$$\begin{bmatrix} x_1^1(k+1) \\ x_2^1(k+1) \\ x_3^1(k+1) \\ x_4^1(k+1) \\ x_5^1(k+1) \\ x_6^1(k+1) \end{bmatrix} = \begin{bmatrix} A_{11}^{11} & 0 & 0 & 0 & 0 & 0 \\ 0 & A_{22}^{11} & 0 & 0 & 0 & 0 \\ 0 & 0 & A_{33}^{11} & 0 & 0 & 0 \\ 0 & 0 & 0 & A_{44}^{11} & 0 & 0 \\ 0 & 0 & 0 & 0 & A_{55}^{11} & 0 \\ 0 & 0 & 0 & 0 & 0 & A_{66}^{11} \end{bmatrix} \begin{bmatrix} x_1^1(k) \\ x_2^1(k) \\ x_3^1(k) \\ x_4^1(k) \\ x_5^1(k) \\ x_6^1(k) \end{bmatrix} +$$
$$\begin{bmatrix} 0 & A_{12}^{11} & 0 & 0 & 0 & 0 \\ A_{21}^{11} & 0 & A_{23}^{11} & A_{24}^{11} & 0 & A_{26}^{11} \\ 0 & A_{32}^{11} & 0 & 0 & A_{35}^{11} & A_{36}^{11} \\ 0 & A_{42}^{11} & 0 & 0 & A_{45}^{11} & A_{46}^{11} \\ 0 & 0 & A_{53}^{11} & A_{54}^{11} & 0 & A_{56}^{11} \\ 0 & A_{62}^{11} & A_{63}^{11} & A_{64}^{11} & A_{65}^{11} & 0 \end{bmatrix} \begin{bmatrix} x_1^1(k) \\ x_2^1(k) \\ x_3^1(k) \\ x_4^1(k) \\ x_5^1(k) \\ x_6^1(k) \end{bmatrix} + \begin{bmatrix} B_1^1 & 0 & 0 & 0 & 0 & 0 \\ 0 & B_2^1 & 0 & 0 & 0 & 0 \\ 0 & 0 & B_3^1 & 0 & 0 & 0 \\ 0 & 0 & 0 & B_4^1 & 0 & 0 \\ 0 & 0 & 0 & 0 & B_5^1 & 0 \\ 0 & 0 & 0 & 0 & 0 & B_6^1 \end{bmatrix} \begin{bmatrix} u_1^1(k) \\ u_2^1(k) \\ u_3^1(k) \\ u_4^1(k) \\ u_5^1(k) \\ u_6^1(k) \end{bmatrix} + \begin{bmatrix} v_1^1(k) \\ v_2^1(k) \\ v_3^1(k) \\ v_4^1(k) \\ v_5^1(k) \\ v_6^1(k) \end{bmatrix}. \tag{3.8}$$

For a more complex scenario, Figure 3.11 shows a distributed environment with five houses with different plans and with different zones that may thermally interact. Remark that as described in the sequel, adjacent areas can be doubly coupled, thermally and by the power constraint. In Figure 3.11, u_i represents the input (heat/cooling power) and y_i is the output vector containing the temperatures/states inside the several divisions of house (i)

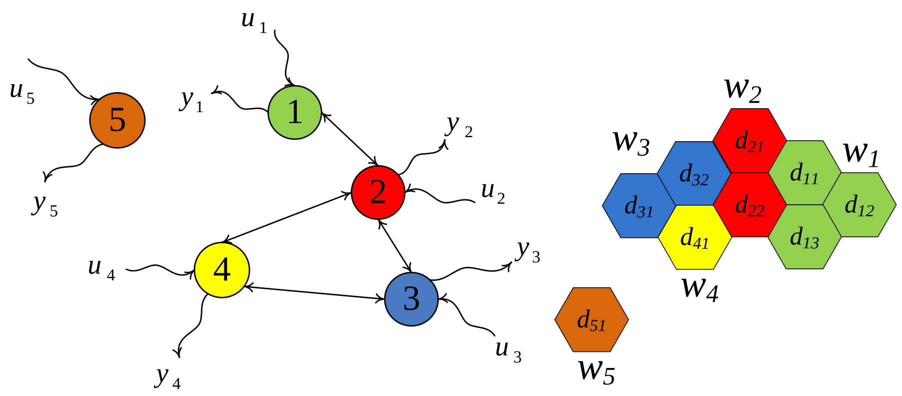

Figure 3.11. Generalized house/TCA scheme example.

Thus, (3.4) can be generalized and presented as:

$$x_1^1(k+1) = A_{11}^{11}x_1^1(k) + A_{12}^{11}x_2^1(k) + A_{13}^{11}x_3^1(k) + A_{11}^{12}x_1^2(k) + A_{12}^{12}x_2^2(k) + B_1^1u_1^1(k) + v_1^1(k),$$

$$x_2^1(k+1) = A_{22}^{11}x_2^1(k) + A_{21}^{11}x_1^1(k) + A_{23}^{11}x_3^1(k) + B_2^1u_2^1(k) + v(k),$$

$$x_3^1(k+1) = A_{33}^{11}x_3^1(k) + A_{32}^{11}x_2^1(k) + A_{31}^{11}x_1^1(k) + A_{32}^{12}x_2^2(k) + B_3^1u_3^1(k) + v_3^1(k),$$

$$x_1^2(k+1) = A_{11}^{22}x_1^2(k) + A_{12}^{22}x_2^2(k) + A_{11}^{21}x_1^1(k) + B_1^2u_1^2(k) + v_1^2(k),$$

$$\begin{aligned} x_2^2(k+1) = {} & A_{22}^{22}x_2^2(k) + A_{21}^{22}x_1^2(k) + A_{21}^{21}x_1^1(k) + \\ & A_{23}^{21}x_3^1(k) + A_{22}^{23}x_2^3(k) + A_{21}^{24}x_1^4(k) + B_2^2u_2^2(k) + v_2^2(k), \end{aligned} \tag{3.9}$$

$$x_1^3(k+1) = A_{11}^{33}x_1^3(k) + A_{12}^{33}x_2^3(k) + A_{11}^{34}x_1^4(k) + B_1^3u_1^3(k) + v_1^3(k),$$

$$x_2^3(k+1) = A_{22}^{33}x_2^3(k) + A_{21}^{33}x_1^3(k) + A_{21}^{34}x_1^4(k)A_{21}^{32}x_1^2(k) + A_{22}^{32}x_2^2(k) + B_2^3u_2^3(k) + v_2^3(k),$$

$$x_1^4(k+1) = A_{11}^{44}x_1^4(k) + A_{11}^{43}x_1^3(k) + A_{12}^{43}x_2^3(k)A_{12}^{42}x_2^2(k) + B_1^4u_1^4(k) + v_1^4(k),$$

$$x_1^5(k+1) = A_{11}^{55}x_1^5(k) + B_1^5u_1^5(k) + v_1^5(k),$$

$$\begin{bmatrix} x_1^1(k+1) \\ x_2^1(k+1) \\ x_3^1(k+1) \\ x_1^2(k+1) \\ x_2^2(k+1) \\ x_1^3(k+1) \\ x_2^3(k+1) \\ x_1^4(k+1) \\ x_1^5(k+1) \end{bmatrix} = \begin{bmatrix} A_{11}^{11} & A_{12}^{11} & A_{13}^{11} & A_{11}^{12} & A_{12}^{12} & 0 & 0 & 0 & 0 \\ A_{21}^{11} & A_{22}^{11} & A_{23}^{11} & 0 & 0 & 0 & 0 & 0 & 0 \\ A_{31}^{11} & A_{31}^{11} & A_{33}^{11} & A_{32}^{12} & 0 & 0 & 0 & 0 & 0 \\ A_{11}^{21} & 0 & 0 & A_{11}^{22} & A_{12}^{22} & 0 & 0 & 0 & 0 \\ A_{21}^{21} & 0 & A_{23}^{21} & A_{21}^{21} & A_{22}^{22} & 0 & A_{22}^{23} & A_{21}^{24} & 0 \\ 0 & 0 & 0 & 0 & 0 & A_{11}^{33} & A_{12}^{33} & A_{11}^{34} & 0 \\ 0 & 0 & 0 & A_{21}^{32} & A_{22}^{32} & A_{21}^{33} & A_{22}^{33} & A_{21}^{34} & 0 \\ 0 & 0 & 0 & A_{12}^{42} & 0 & A_{11}^{43} & A_{12}^{43} & A_{11}^{44} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & A_{11}^{55} \end{bmatrix} \begin{bmatrix} x_1^1(k) \\ x_2^1(k) \\ x_3^1(k) \\ x_1^2(k) \\ x_2^2(k) \\ x_1^3(k) \\ x_2^3(k) \\ x_1^4(k) \\ x_1^5(k) \end{bmatrix} +$$

$$+ \begin{bmatrix} B_1^1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & B_2^1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & B_3^1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & B_1^2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & B_2^2 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & B_1^3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & B_2^3 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & B_1^4 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & B_1^5 \end{bmatrix} \begin{bmatrix} u_1^1(k) \\ u_2^1(k) \\ u_3^1(k) \\ u_1^2(k) \\ u_2^2(k) \\ u_1^3(k) \\ u_2^3(k) \\ u_1^4(k) \\ u_1^5(k) \end{bmatrix} + \begin{bmatrix} v_1^1(k) \\ v_2^1(k) \\ v_3^1(k) \\ v_1^2(k) \\ v_2^2(k) \\ v_1^3(k) \\ v_2^3(k) \\ v_1^4(k) \\ v_1^5(k) \end{bmatrix}.$$

Chapter 4

MPC and PI control in thermal comfort systems

4.1 Introduction

The chapter presents the first approach towards the final developed control structure. It allowed us to understand the problem, its dynamics and to verify that the MPC control strategy is suitable for the objective that is intent to be achieved. So, it considers one house/TCA and no communication with neighbouring is taking into account (Barata et al., 2012a).

The methodologies are based on a predictive control structure associated to a PI controller and applied to the thermal house comfort in an environment with limited energy sources. Thus, the available and necessary power to cool and heat the house within the desire “comfort zone” is partially available and, consequently constrained. The system also uses the house thermal inertia to “accommodate thermal energy” within the selected temperature range, maintaining the comfort when no energy is available and reducing the energy consumption without loss of the thermal comfort. The simulation results obtained with traditional PI and with MPC are presented and it can be seen that the system is able to provide high-energy conservation and reliable comfort. The house temperature variations are calculated and are taking into account the necessary heat and cooling needs and heat losses to the environment. The indoor temperature time derivative is expressed as follows,

$$\frac{dT_l^i}{dt} = \frac{1}{C_{l_{eq}}^i}\left(Q_{l\,heat}^i - Q_{l_{losses}}^i + Q_{l_{Pd}}^i\right). \tag{4.1}$$

Actually (4.1) is not an accurate model of the house. Nevertheless, it reflects well enough the dominant model of a real house to be used for designing the MPC controller.

The heat loss is mainly a function of outdoor air temperature. By taking the outdoor temperature as a primary influencing factor for the weather, the heat loss is given by,

$$Q^i_{l_{losses}} = \frac{T_{out} - T^i_l}{R^i_{l_{eq}}}. \tag{4.2}$$

The parameter $R^i_{l_{eq}}$ describes the equivalent thermal resistance of all walls (including roof and ceiling) and windows that isolate the house from outside, and can be describe as a electrical parallel resistance circuit (Gulley and Chistol, 2006; Ma, et al., 2012).

$$R^i_{l_{eq}} = R^i_{l_{walls}} // R^i_{l_{windows}}. \tag{4.3}$$

As also used in (Löhnberg, 1999; Mendes, *et al*., 2001), the external temperature disturbance variation, T_{out}, can be approximated represented by a sine (with a given amplitude) where is added a constant temperature value. Other disturbances can be reflected in (4.1), like heat flux from solar radiation, inside loads generated by occupancy, lights or other electrical devices (Ma, et al., 2012).

The plant model representation (4.1) can be rewritten and changed into a discrete model.

$$y(k+1) = ay(k) + bu(k) + cv(k), \tag{4.4}$$

where, $a = \left(1 - \frac{\Delta t}{R^i_{l_{eq}} C^i_{l_{eq}}}\right)$, $b = \frac{\Delta t}{C^i_{l_{eq}}}$, $c = \frac{\Delta t}{R^i_{l_{eq}} C^i_{l_{eq}}}$, u(k) is the necessary heat/cooling power, v(k) are the disturbances and y(k) is the indoor temperature. Note that the space is cooled when u(k) < 0 and heated when u(k) > 0.

4.2 System description

As a first approach towards developing a control structures it is considered an individual house, Figure 4.1. As mentioned, this approach does not take into account the possibility of communication with neighbouring houses.

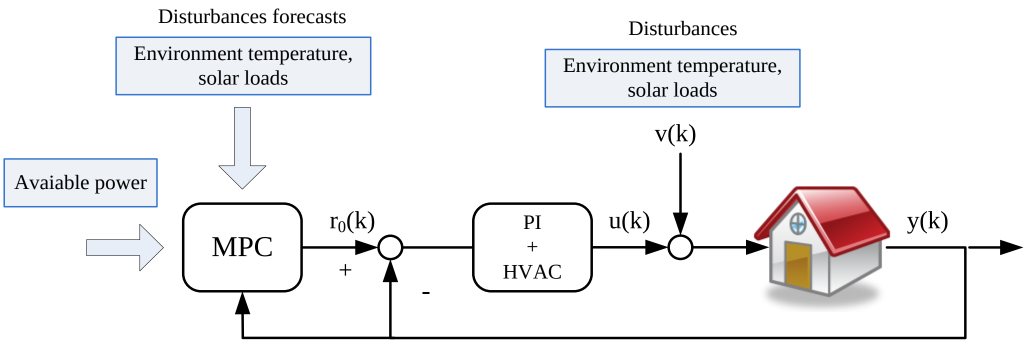

Figure 4.1. Block diagram of the implemented system.

The following discrete equations describe the implemented system showed in Figure 4.1.

$$Y(z) = \frac{b}{z-a}U(z) + \frac{c}{z-a}V(z). \tag{4.5}$$

With the controller described by,

$$PI = k_p + \frac{k_i z}{z-1} = \frac{z(k_p + k_i) - k_p}{z-1}. \tag{4.6}$$

Being

$$U(z) = k\frac{z-\beta}{z-1}E(z), \tag{4.7}$$

and

$$E(z) = R_0(z) - Y(z). \tag{4.8}$$

Figure 4.1 can also be characterized by the following discrete equations, where (4.9) and (4.10) describe the system and (4.11) and (4.12) the controller.

$$x(k+1) = Ax(k) + Bu(k) + Ev(k), \tag{4.9}$$

$$y(k) = Cx(k), \tag{4.10}$$

$$\xi(k+1) = A_c\xi(k) + B_c[r(k) - y(k)], \tag{4.11}$$

$$u(k) = C_c\xi(k). \tag{4.12}$$

Substituting (4.12) in (4.9) and (4.10) in (4.11) results in (4.13) and (4.14), respectively that describe the close-loop system in u(k).

$$x(k+1) = Ax(k) + BC_c\xi(k) + Ev(k), \tag{4.13}$$

$$\xi(k+1) = A_c\xi(k) + B_c[r(k) - Cx(k)], \tag{4.14}$$

$$\begin{bmatrix} x(k+1) \\ \xi(k+1) \end{bmatrix} = \begin{bmatrix} A & BC_c \\ -B_cC & A_c \end{bmatrix} \begin{bmatrix} x(k) \\ \xi(k) \end{bmatrix} + \begin{bmatrix} 0 \\ B_c \end{bmatrix} r(k) + \begin{bmatrix} E \\ 0 \end{bmatrix} v(k). \tag{4.15}$$

The following equations describe the close-loop system $\Delta r(k)$

$$r(k) = \Delta r(k) + r(k-1), \tag{4.16}$$

$$x(k+1) = Ax(k) + BC_c\xi(k) + Ev(k). \tag{4.17}$$

Equation (4.18) results from substituting (4.16) in (4.14).

$$\xi(k+1) = A_c\xi(k) - B_cCx(k) + B_c[\Delta r(k) - r(k-1)], \tag{4.18}$$

with

$$\gamma(k) = r(k-1), \tag{4.19}$$

$$\gamma(k+1) = \gamma(k) + \Delta r(k), \tag{4.20}$$

$$x(k+1) = Ax(k) + BC_c\xi(k) + Ev(k). \tag{4.21}$$

Substituting (4.20) in (4.18) results in

$$\xi(k+1) = -B_cCx(k) + A_c\xi(k) + B_c\gamma(k) + B_c\Delta r(k), \tag{4.22}$$

$$\begin{bmatrix} x(k+1) \\ \xi(k+1) \\ \gamma(k+1) \end{bmatrix} = \overbrace{\begin{bmatrix} A & BC_c & 0 \\ -B_cC & A_c & B_C \\ 0 & 0 & I \end{bmatrix}}^{A_1} \overbrace{\begin{bmatrix} x(k) \\ \xi(k) \\ \gamma(k) \end{bmatrix}}^{\zeta(k)} + \overbrace{\begin{bmatrix} 0 & E \\ B_C & 0 \\ I & 0 \end{bmatrix}}^{[B_1\ B_2]} \begin{bmatrix} \Delta r_0(k) \\ v(k) \end{bmatrix}, \tag{4.23}$$

$$y(k) = \left[\underbrace{C \quad 0 \quad 0}_{C_y}\right] \begin{bmatrix} x(k) \\ \xi(k) \\ \gamma(k) \end{bmatrix}, \tag{4.24}$$

$$u(k) = \left[\underbrace{0 \quad C_c \quad 0}_{C_u}\right] \begin{bmatrix} x(k) \\ \xi(k) \\ \gamma(k) \end{bmatrix}, \tag{4.25}$$

$$r = [0 \quad 0 \quad I] \begin{bmatrix} x(k) \\ \xi(k) \\ \gamma(k) \end{bmatrix}, \tag{4.26}$$

Or,

$$\xi(k+1) = A_1\zeta(k) + B_1\Delta r_0(k) + B_2v(k), \tag{4.27}$$

$$y(k) = C_y \zeta(k) \quad u(k) = C_u \zeta(k). \tag{4.28}$$

As mentioned in Chapter 2.3 predictive control is based on the receding horizon principle in which, at each sample interval, the current controller output is obtained by solving an optimal control problem of finite horizon. The input to the controller is current output/state information and the output is a sequence of future control actions where usually the first element in the sequence is applied to the plant.

Predictive control belongs to the class of model-based designs where a model of the plant is used to predict the behaviour of the plant and calculate the controller output such that a given control criterion is minimized.

The criterion must be selected such that the performance and robustness specifications are accomplished. The GPC criterion introduced in (Clarke et al., 1987) is of the form:

$$J = \sum_{i=1}^{n} \left[\sum_{l=1}^{H_P} \left\| y_i(k+l) - y_i^d(k+l) \right\|_{Q_i}^2 + \sum_{l=1}^{N_C} \| \Delta u_i(k+l-1) \|_{R_i}^2 \right], \tag{4.29}$$

where $\mathbf{Q_i}$ and $\mathbf{R_i}$ are weight matrices, H_P, $N_C \in$ N are predictive horizon and control horizon, respectively, and $H_P \geq M$, y_i^d is the set-point of subsystem $\boldsymbol{S_i}$, $\Delta u_i(k) = u_i(k) - \Delta u_i(k-1)$ is the input increment vector of subsystem $\boldsymbol{S_i}$.

Considering Figure 4.1, (4.29) can be rewritten,

$$J = \sum_{i=1}^{n} \left[\sum_{l=1}^{H_P} \left\| y_i(k+l) - r_i^d(k+l) \right\|_{Q_i}^2 + \sum_{l=1}^{N_C} \| \Delta ro_i(k+l-1) \|_{R_i}^2 \right]. \tag{4.30}$$

Then the model outputs in future sample intervals are given as follows:

$$\hat{y} = \begin{bmatrix} \hat{y}(k+1) \\ \hat{y}(k+2) \\ \vdots \\ \hat{y}(k+H_P) \end{bmatrix} = \begin{bmatrix} \hat{y}_o(k+1) \\ \hat{y}_o(k+2) \\ \vdots \\ \hat{y}_o(k+H_P) \end{bmatrix} + \begin{bmatrix} g_1 & 0 & \dots & 0 \\ g_2 & g_1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ g_{H_P} & g_{H_P-1} & \cdots & g_{H_P-N_C-1} \end{bmatrix} \times \begin{bmatrix} \Delta ro(k) \\ \Delta ro(k+1) \\ \vdots \\ \Delta ro(k+N_C-1) \end{bmatrix}. \tag{4.31}$$

Where,

$$\begin{bmatrix} \hat{y}_o(k+1) \\ \hat{y}_o(k+2) \\ \vdots \\ \hat{y}_o(k+H_P) \end{bmatrix} = \begin{bmatrix} C_1A_1 & C_2A_2 & \dots & C_nA_n \\ C_1{A_1}^2 & C_2{A_2}^2 & \ddots & C_n{A_n}^2 \\ \vdots & \vdots & \ddots & \vdots \\ C_1{A_1}^{H_P} & C_2{A_2}^{H_P} & \dots & C_n{A_n}^{H_P} \end{bmatrix} \begin{bmatrix} xo(k) \\ xo(k+1) \\ \vdots \\ xo(k+N_C-1) \end{bmatrix} + \begin{bmatrix} w_1 & 0 & \dots & 0 \\ w_1 & w_1 & \ddots & \vdots \\ \vdots & \vdots & \ddots & 0 \\ w_{H_P} & w_{H_P-1} & \dots & w_{H_P-N_C-1} \end{bmatrix} \begin{bmatrix} v(k) \\ v(k+1) \\ \vdots \\ v(k+N_C-1) \end{bmatrix}. \tag{4.32}$$

In compact form, (4.31) and (4.32) can be written as the following relations:

$$\hat{Y} = \hat{Y}_o + G\Delta R_o, \tag{4.33}$$

$$\hat{Y}_0 = CAx_0 + Wv. \tag{4.34}$$

Being the prediction error e determined using the following equation,

$$e = \hat{y} - r_d, \tag{4.35}$$

where r_d is the set-point. Substituting (4.33) in (4.35), and the result in (4.30), the objective function can be presented in the form,

$$J(\Delta Ro) = \left(\hat{Y}_o + G\Delta Ro - R_d\right)^T Q\left(\hat{Y}_o + G\Delta R_o - R_d\right) + \Delta Ro^T R \Delta Ro. \tag{4.36}$$

The solution minimising J to give the optimal suggested control increment R_o^*, in the absence of constrains, is given by $\frac{\partial J}{\partial \Delta Ro}$, resulting,

$$\Delta R_o^* = (G^T Q G + R)^{-1} G^T Q\left(R_d - \hat{Y}_o\right). \tag{4.37}$$

To simulate the system it was considered, that the house dynamics is represented by (4.38) and the PI controller by (4.39), respectively.

$$\frac{K_{Plant}}{\tau_{Plant}\, s + 1}, \tag{4.38}$$

$$K_{PI}\left(1 + \frac{1}{\tau_{PI}\, s}\right). \tag{4.39}$$

With K_{Plant} and τ_{Plant} are the house and K_{PI} and $\tau_{PI}$the controller parameters. Applying the above FT's in Figure 4.1, and analysing in separated each one of the entries, with and without perturbation, results the in next equations (4.40) and (4.41), respectivly.

$$\frac{K_{Plant}\tau_{PI}\, s}{\tau_{PI}\,\tau_{Plant}\, s^2 + \tau_{PI}\, s(1 + K_{Plant}K_{PI}) + K_{Plant}K_{PI}}, \tag{4.40}$$

$$\frac{K_{Plant}K_{PI}(1+\tau_{PI}\,s)}{\tau_{PI}\,\tau_{Plant}\,s^2+\tau_{PI}\,s(1+K_{Plant}K_{PI})+K_{Plant}K_{PI}}. \tag{4.41}$$

Converting the system to discrete space–state model, the augmented space-state model is given by A_i , B_i and C_i. resulting matrixes are presented in the following format.

$$\begin{bmatrix} x(k+1) \\ u(k) \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x(k) \\ u(k-1) \end{bmatrix} + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u(k), \tag{4.42}$$

$$y(k) = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x(k) \\ u(k-1) \end{bmatrix}, \tag{4.43}$$

where A, B and C results from continuous to discrete space-state transformation using Zero Order Hold (ZOH) (Rugh, 1996).

According to the above showed, the equations (4.33) and (4.34) parameters can assume now the final form and can be written as follow.

$$CA = \begin{bmatrix} C_iA_i & C_iA_i & \dots & C_iA_i \\ C_iA_i{}^2 & C_{i2}A_i{}^2 & \ddots & C_iA_i{}^2 \\ \vdots & \vdots & \ddots & \vdots \\ C_iA_i{}^{H_P} & C_iA_i{}^{H_P} & \dots & C_iA_i{}^{H_P} \end{bmatrix}, \tag{4.44}$$

$$G = \begin{bmatrix} C_{i1}B_{1i} & 0 & 0 & \dots & \dots & 0 \\ C_iA_iB_{1i} & C_{i1}B_{1i} & 0 & \dots & \dots & 0 \\ C_iA_i{}^2B_{1i} & C_iA_iB_{1i} & C_{i1}B_{1i} & 0 & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & \dots & \vdots \\ C_iA_i{}^{H_P-2}B_{1i} & C_iA_i{}^{H_P-3}B_{1i} & C_iA_i{}^{H_P-4}B_{1i} & \dots & 0 & 0 \\ C_iA_i{}^{H_P-1}B_{1i} & C_iA_i{}^{H_P-2}B_{1i} & C_iA_i{}^{H_P-3}B_{1i} & \dots & C_iA_iB_{1i} & C_{i1}B_{1i} \end{bmatrix}, \tag{4.45}$$

$$W = \begin{bmatrix} C_{i1}B_{2i} & 0 & 0 & \dots & \dots & 0 \\ C_iA_iB_{2i} & C_{i1}B_{2i} & 0 & \dots & \dots & 0 \\ C_iA_i{}^2B_{2i} & C_iA_iB_{2i} & C_{i1}B_{2i} & 0 & \dots & \vdots \\ \vdots & \vdots & \vdots & \dots & \dots & \vdots \\ C_iA_i{}^{H_P-2}B_{2i} & C_iA_i{}^{H_P-3}B_{2i} & C_iA_i{}^{H_P-4}B_{2i} & \dots & 0 & 0 \\ C_iA_i{}^{H_P-1}B_{2i} & C_iA_i{}^{H_P-2}B_{2i} & C_iA_i{}^{H_P-3}B_{2i} & \dots & C_iA_iB_{2i} & C_{i1}B_{2i} \end{bmatrix}, \tag{4.46}$$

where B_{1i} and B_{2i} emerge from matrix B_i corresponding each one to one of the system inputs.

Rewriting (4.33) and (4.34) results in,

$$\hat{Y} = \hat{Y_o} + G\Delta R_0\,, \tag{4.47}$$

$$\hat{Y_o} = \Gamma_y\zeta(k) + W_y v. \tag{4.48}$$

From matrices $\mathbf{T}(\tilde{C},\tilde{A})$ and $\mathrm{L}(\tilde{C},\tilde{A},\tilde{B})$ below,

$$\boldsymbol{T}(\tilde{C},\tilde{A}) = \begin{bmatrix} \tilde{C}\tilde{A} \\ \tilde{C}\tilde{A}^2 \\ \vdots \\ \tilde{C}\tilde{A}^{H_P} \end{bmatrix}, \tag{4.49}$$

$$\mathcal{L}(\tilde{C},\tilde{A},\tilde{B}) = \begin{bmatrix} \tilde{C}\tilde{A} & 0 & \dots & 0 \\ \tilde{C}\tilde{A}\tilde{B} & \tilde{C}\tilde{A} & \dots & 0 \\ \tilde{C}\tilde{A}^2\tilde{B} & \tilde{C}\tilde{A}\tilde{B} & 0 & \vdots \\ \vdots & \vdots & \dots & \vdots \\ \tilde{C}\tilde{A}^{H_P-2}\tilde{B} & \tilde{C}\tilde{A}^{H_P-3}\tilde{B} & \dots & 0 \\ \tilde{C}\tilde{A}^{H_P-1}\tilde{B} & \tilde{C}\tilde{A}^{H_P-2}\tilde{B} & \dots & \tilde{C}\tilde{A} \end{bmatrix}. \tag{4.50}$$

The matrices G, W_y and Γ_y can be obtained and formalized as:

$$\Gamma_y = T(C_y, A_1),\ \Gamma_u = T(C_u, A_1), \tag{4.51}$$

$$W_y = \mathcal{L}(C_y, A_1, B_2) \text{ and } W_u = \mathcal{L}(C_u, A_1, B_2), \tag{4.52}$$

$$G = \mathcal{L}(C_y, A_1, B_1),\ G_u = \mathcal{L}(C_u, A_1, B_1). \tag{4.53}$$

As mentioned above, the control is now made with constrains to find the $\Delta r_0(k)$ that minimize the cost function presented in (4.54). Assuming that the available energy is conditioned, the control method intent to restrict the value of the heating/cooling user power demanding, u. The designed, Figure 4.2 system also includes constrains in upper and lower value of Δr_0 and r_0.

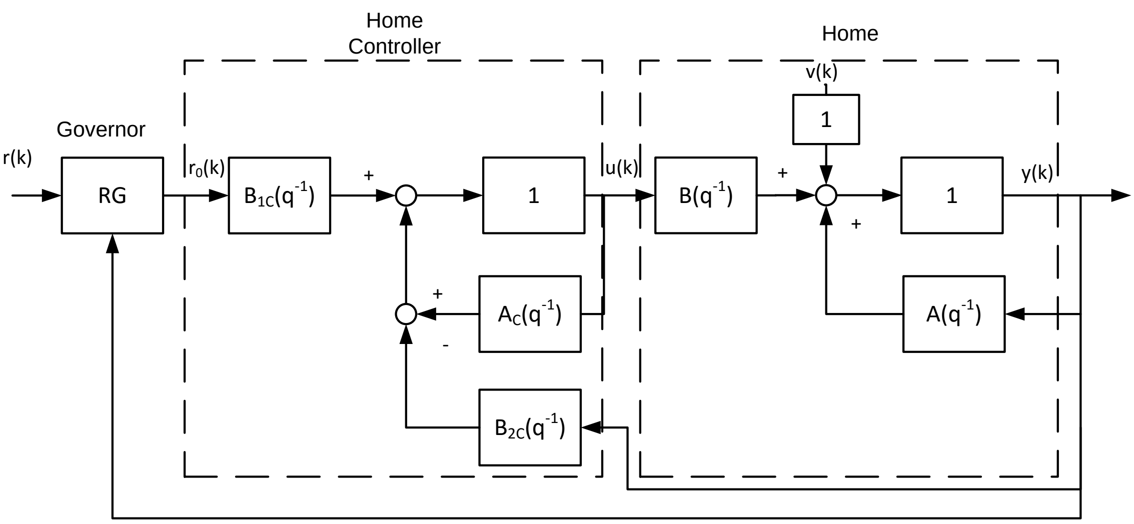

Figure 4.2. MPC with constraints, system block diagram.

The predictive controller can be posed as a quadratic programming problem, where,

$$\min_{\Delta R_0} J(k) = \left(\widehat{Y_o} + G\Delta R_0 - R_d\right)^T Q_e\left(\widehat{Y_o} + G\Delta R_0 - R_d\right) + \Delta R_0^T R_e \Delta R_0, \tag{4.54}$$

is to be optimized, subject to the constraints (4.55)-(4.59):

$$y(k) = A(q^{-1})y(k-1) + B(q^{-1})u(k-1) + C(q^{-1})v(k-1), \tag{4.55}$$

$$u(k) = A_c(q^{-1})u(k-1) + B_{1c}(q^{-1})r_0(k) - B_{2c}(q^{-1})y(k), \tag{4.56}$$

$$\underline{r_o}(k) \leq r_o(k) \leq \overline{r}_o(k), \tag{4.57}$$

$$\Delta\underline{r_o}(k) \leq \Delta r_o(k) \leq \Delta\overline{r}_o(k), \tag{4.58}$$

$$\underline{u}(k) \leq u(k) \leq \overline{u}(k). \tag{4.59}$$

Developing (4.54), the new cost function can be written as (Igreja and Cruces, 2002)

$$\min_{\Delta R_0} J = \left(\frac{1}{2}\Delta R_0^T Q_u \Delta R_0\right) + C_u^T \Delta R_0, \tag{4.60}$$

with

$$Q_u = 2(G^T Q_e G + R_e), \tag{4.61}$$

And

$$C_u^T = -2\left(R_d - \widehat{Y_o}\right)^T Q_e . G. \tag{4.62}$$

The constrains can be expressed in terms of control movements resulting,

$$\underline{R}_0 \leq T_l \Delta R_0 + [I_m \dots I_m] r_o(t-1) \leq \overline{R}_0 \,, \tag{4.63}$$

$$\Delta\underline{R}_0 \leq \Delta R \leq \Delta\overline{R}_0, \tag{4.64}$$

$$\underline{U} \leq G\Delta R_0 + \widehat{U_O} \leq \overline{U}, \tag{4.65}$$

where T_l is a lower triangular matrix whose non null submatrices are I_m the identity matrix. Introducing the new variable,

$$X = T_l \Delta R_o + \Pi \,. \tag{4.66}$$

$$\Pi = [I_m \dots I_m] r_o(k-1) - \underline{R_0}. \tag{4.67}$$

ΔR_o becomes,

$$\Delta R_o = V(X - \Pi), \tag{4.68}$$

$$V = T_l^{-1}. \tag{4.69}$$

And consequently (4.60) becomes,

$$\min_{\Delta R_0} J = \left(\frac{1}{2} X^T Q_X X\right) + C_X^T X, \tag{4.70}$$

$$Q_x = V^T Q_u V = 2V^T(G^T Q_e G + R_e)V, \tag{4.71}$$

and

$$C_x^T = C_u^T - \Pi^T V^T Q_u V = -2\Pi^T V^T (G^T Q_e G + R_e)V. \tag{4.72}$$

Finally, the constrains can be expressed as,

$$\begin{bmatrix} I \\ -V \\ V \\ -G_u V \\ G_u V \end{bmatrix} X \leq \begin{bmatrix} \overline{R}_0 - \underline{R}_0 \\ -\Delta \underline{R}_0 - V\Pi \\ \Delta \overline{R}_0 + V\Pi \\ -\underline{U} - G_u V\Pi + \widehat{U}_O \\ \overline{U} + G_u V\Pi - \widehat{U}_O \end{bmatrix}. \tag{4.73}$$

The QP solution can be obtained using a modified Lemke's method (Camacho, 1993; Igreja and Cruces, 2002).

Remark: the predicted needed power is given by (4.74).

$$\widehat{U}_O = \Gamma_u \zeta(k) + W_u v, \tag{4.74}$$

where, the only active state in Γ_u is the one that corresponds to *u* in $\zeta(k)$. Matrices W_u and Γ_u are showed in annex. With this formalization, constrains can be directly applied taking into account the limited power variation along time.

4.3 Results

As mentioned, it was created a temperature "comfort zone". This approach allows to weight only the temperatures outside the gap, instead of traditional system were all deviations are weight, and consequently, more resources are needed. Also, in order to reduce the energy needs, it was defined that $u(k)=0$ inside the temperature bound. It is considered a comfort zone if the indoor reference is e_T relatively to the reference temperature. Two situations are here presented and the obtained results can be seen in Chapter 4.3.2. In the first situation is considered that outside the comfort zone, the system calculates $u(k)$ and the cost function *J*, and, inside the comfort zone both *u* and *J* are null. The second situation it is distinguished from the first one because it considers that inside the comfort zone, the cost function J can always assume the optimal value.

The generalised cost function can be written as (4.75).

$$J(k) = \sum_{l=1}^{H_P} \|e(k+l)\|_{Q_e}^2 + \sum_{l=1}^{N_C} \|\Delta r_0(k+l-1)\|_{R_e}^2 \Bigg], \tag{4.75}$$

where $\mathbf{Q_e}$ ≥0 and $\mathbf{R_e}$ >0 are weight matrices and depend from $e_{T.}$, $\boldsymbol{H_P}$, $\boldsymbol{N_C} \in \mathbf{N}$ are predictive horizon and control horizon, respectively, with $\boldsymbol{H_P} \geq$ M and, $\Delta r_0(k)$ is the input increment vector.

As mentioned, $\mathbf{Q_e}$ and $\mathbf{R_e}$ depend on e_T value.

$$Q_e \begin{cases} 0 & \|e\| \leq e_T \\ Q & \|e\| > e_T \end{cases} \tag{4.76}$$

$$R_e \begin{cases} 0 & \|e\| \leq e_T \\ R & \|e\| > e_T \end{cases}. \tag{4.77}$$

In the simulated system it is considered that the house is exposed to an additional perturbation, solar incidence, which elevates the outside temperature in more 7 ºC between 15 and 19 hours, Figure 4.3.

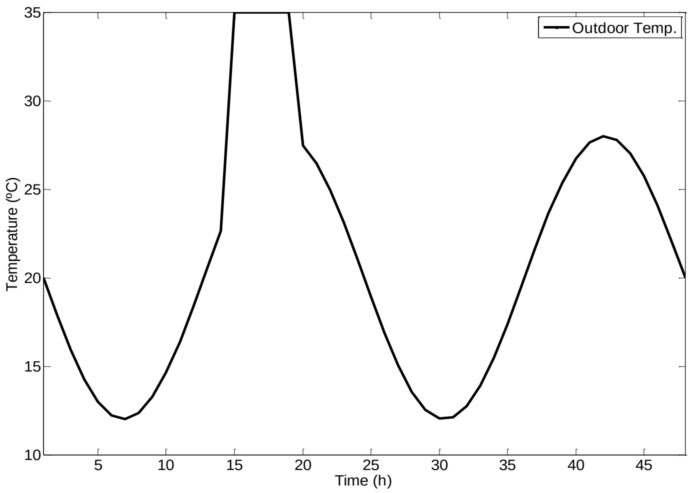

Figure 4.3. Outdoor temperature.

The simulation period is 48 hours and the several approaches are compared. The results are showed in the next subsections and the used parameters are in the table below.

Table 4.1.Simulation parameters for PIvsMPC

Parameter	Value	Units
H_P	24	-
N_C	48	-
Δt	0.5	h
K_{Plant}	1	-
τ_{Plant}	130	-
R	0.1	-
Q	1	-
PI gain (K_{PI})	200	-
PI time const (τ_{PI})	130	s
e_T	0.5	ºC

4.3.1 **PI versus MPC.**

The results and performance with PI controller and with MPC+PI are here analysed, compared and showed in Figure 4.4 to Figure 4.6.

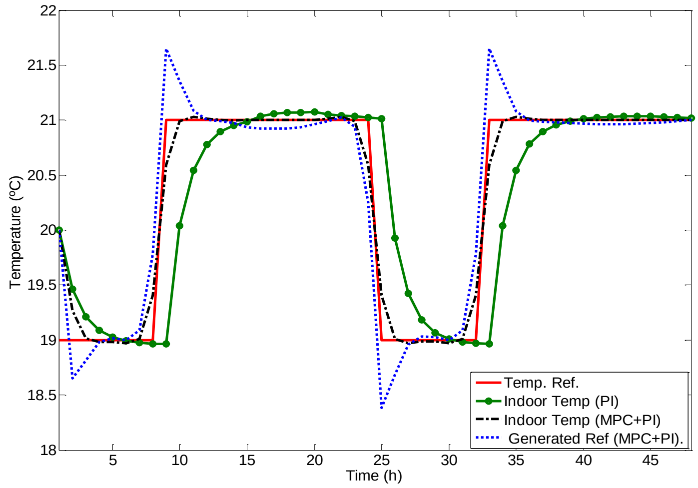

Figure 4.4. Indoor temperature.

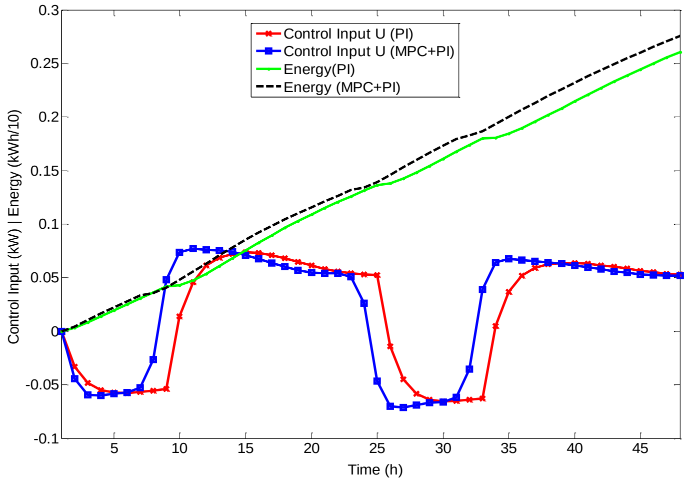

Figure 4.5. Power and energy consumption.

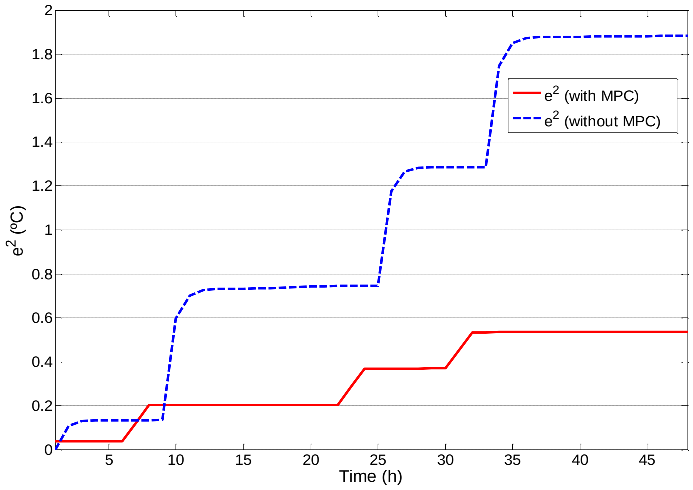

Figure 4.6. Temperature error with and without (MPC).

As can been seen in Figure 4.5 the total energy consumption is very similar, but, the MPC provides the anticipative effect, Figure 4.4, that maintains the indoor temperature always in line with the reference minimizing the error, Figure 4.6, comparatively with the PI solution.

4.3.2 **MPC with "comfort zone"**

As mentioned, here are present the obtained results of two distinguish situations. The "*Case 1*" considered that outside the comfort zone *u* and the cost function are calculated and inside comfort zone both *u* and *J* are null.

The second approach, "*Case 2*", is similar to the first but the cost function *J* is always calculated.

The next table summarize the actions that distinguish both approaches.

Table 4.2. Simplified algorithm for MPC with “comfort zone”.

Case 1	Case 2

if $\|e\| > e_T(0.5ºC)$ **then**
compute u and J
else
u=0 and J=0
end if
	if $\|e\| > e_T(0.5ºC)$ **then**
	compute u and J
	else
	u=0
	compute J
	end if

Figure 4.7 and Figure 4.9 show the results

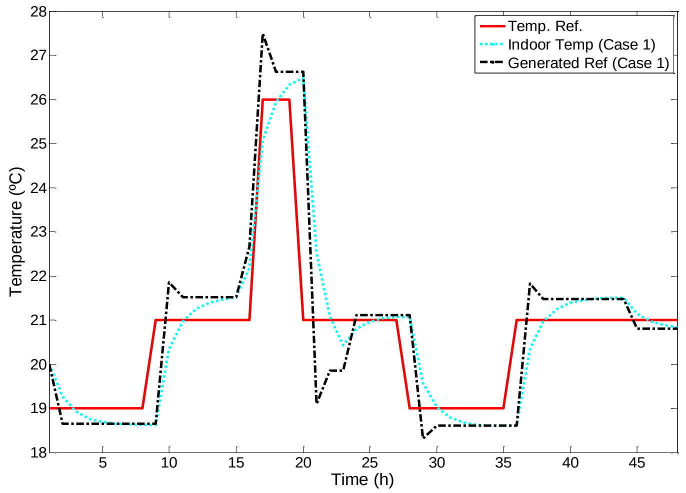

Figure 4.7. Case 1 - Indoor temperature with “comfort zone”.

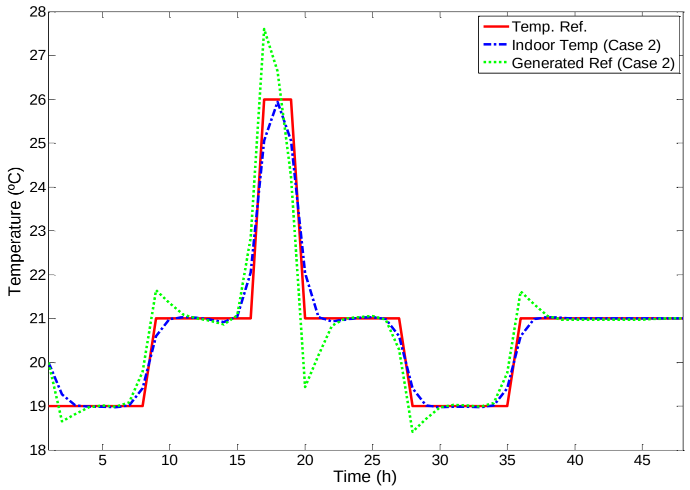

Figure 4.8. Case 2 - Indoor temperature with “comfort zone”.

Figure 4.7 shows that the generated reference "*Case 1*" is constant (no optimal increment is calculated) when the difference between temperatures is within the range, and, due this fact, the MPC anticipative effect is lost.

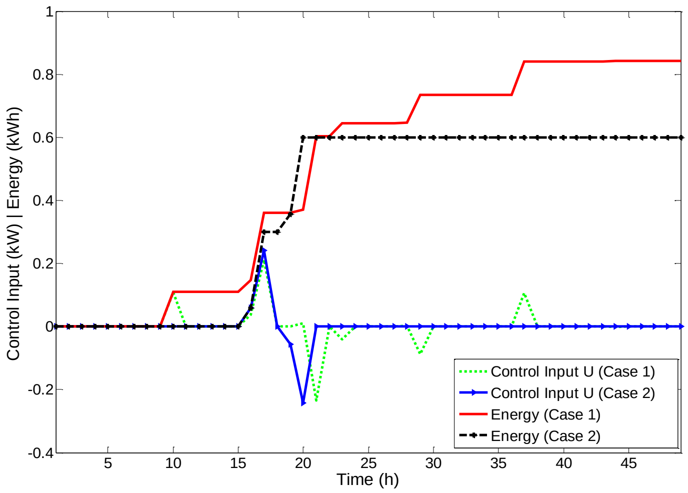

Figure 4.9. Power and energy consumption with "comfort zone".

On the other hand in Figure 4.7 the anticipative effect is maintain in "*Case 2*", and consequently, Figure 4.9 reveals better results with less power "peaks" and also with less energy expended comparatively with "*Case 1*".

4.3.3 MPC with "comfort zone" and constrained available power

The results presented in this item consider that the available power is limited and variable.

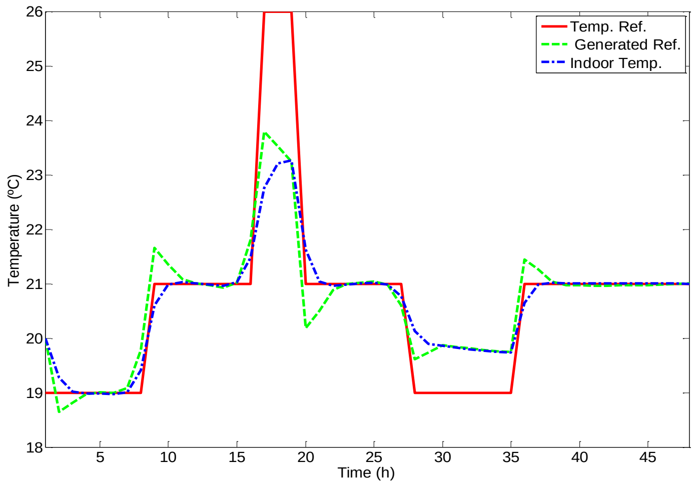

Figure 4.10. Indoor temperature evolution with limited power.

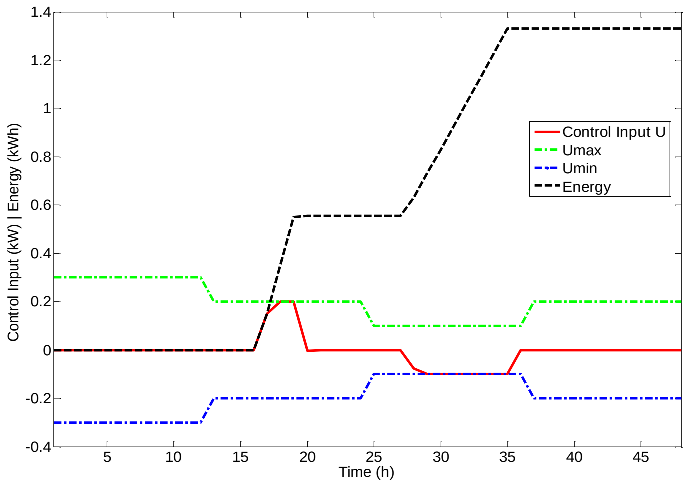

Figure 4.11. Power and energy consumption with limited power.

In Figure 4.10 can be seen that due the constrained power, Figure 4.11, the indoor temperature cannot always follow the reference. The amount of energy expended grows a bit comparatively with Figure 4.9.

4.3.4 **Conclusions**

In this chapter, in order to provide thermal house comfort, a MPC control technique associated with a inner loop PI was presented.

It could be observed through the simulations and analysis results that good performances were obtain by both approaches (with and without MPC). In general the error and the energy consumption were considerably reduced with the MPC implementation.

In particular, results show that in the "comfort zone" MPC controller reduces considerably the energy consumption with less power "peaks".

The MPC power constrained shows that the approach can find a fair trade-off due to the combination of the anticipative effect with available power, in order to maintain the temperature near to the comfort zone, even when indoor temperature cannot follow the desire reference.

Chapter 5

Thermal Comfort with Demand Side Management Using Distributed MPC

5.1 Introduction

Emerging new technologies like distributed generation, distributed storage, and demand-side load management will change the way we consume and produce energy. These techniques enable the possibility to reduce the greenhouse effects and improve grid stability, balancing the demand and supply. Also, the reduction in CO_2 emissions and the introduction of renewable sources based generation have become important topics today. However, these renewable resources are mainly given by very fluctuating and uncontrollable sun, water, and wind power. The work here presented intends to support the expected introduction of a large penetration level of renewable sources, in particularly providing a solution for implementation in an environment where buildings are mainly supplied by this type of resource. Especially because, reducing energy consumption in buildings is a trend in the world today due to economic aspects or environmental reasons. This chapter presents a DMPC for indoor thermal comfort which simultaneously optimizes the consumption of a limited shared energy resource. The control objective of each subsystem is to minimize the heating/cooling energy cost while maintaining the indoor temperature and consumed power inside bounds. In a distributed coordinated environment, the control uses multiple dynamically coupled agents (one for each subsystem/house) aiming to achieve satisfaction of coupling constraints. In accordance with the hourly power demand profile, each house assigns a priority level indicating how much is willing to bid in auction for consumption of limited clean resource. This procedure allows the hourly variation of bidding values and, consequently, agent's orders for accessing clean energy also varies. Despite of power constraints, all houses also have thermal comfort constraints that must be fulfilled. The system is simulated with several houses in a distributed environment.

5.2 Implemented global scenario

The scenario considers two types of available energy resources, the *green* and the *red*. The *green* or *clean* resource must always be consumed (it is not disposable), it is limited to a maximum available value and it is considered a time variable resource. In opposition, the *red* is always available and it is considered a *dirty* resource, more expensive than the *green*. Therefore, if the *green* resource is insufficient to satisfy the house's required demand, the *red* must be consumed with an increase in the total energy cost. To encourage *clean* resource consumption, it is considered that *green* energy price per kWh has a maximum auction value and it is always cheaper than the *red* energy price. The agents (one by each house) must bid in an auction (provided by the MO), the price that they are willing to pay to consume the *green* resource. The agents make their bid in the auction with one day ahead to show how much is intended to pay per kWh to consume *green* resource in each one of the next 24 hours. The next dots summarize all assumptions made:

- Divisions must share a limited predictable renewable *green* resource;
- The *green* or clean resource must always be consumed or stored and it is limited to a maximum available that varies in time.
- Agents make their bid in the auction with one day ahead to show how much is intended to pay per kWh for consumption of *green* resource, in each one of the next 24 hours;
- Access to *green* resource is done hourly in accordance to the made bid value. The one that is able to pay more uses the needed stock first, and the second can use only the remaining energy, and so on;
- Outside temperatures, disturbances and daily comfort temperature bounds are known by each system inside the predictive horizon (H_P);
- If the *green* resource is insufficient to satisfy the demand required by the houses/divisions, the *red* resource (from grid) must be consumed;
- The r*ed* resource has a fixed kW price that is always higher than the *green* to promote the renewable energy consumption;

- The consumed *red* resource for comfort purposes implies a penalty in the final cost function (5.1) due to the soft constraint violation, which is imposed by the maximum available *green* resource if exceeded.

The MPC optimization is solved by each TCA at each time step according to the sequential DMPC scheme depicted in Figure 5.1. The *green* available power forecast is received by the agent who made the highest bid (first in the sequential access scheme) and this information is used as power constraint value in (5.10). The agent optimization problem predicts the consumption, subtracts it to the initially received available maximum and passes the information to the next on the sequence list.

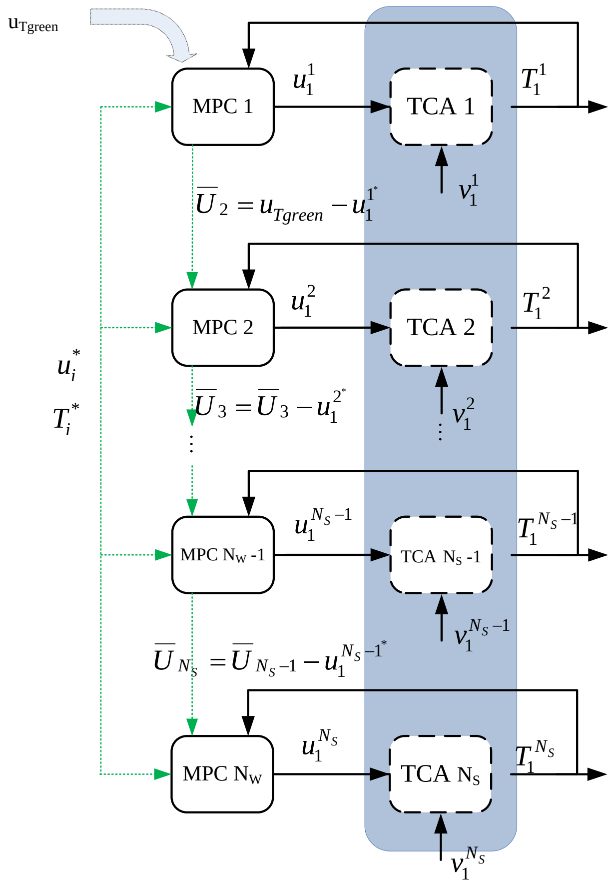

Figure 5.1. Implemented sequential architecture scheme.

In Figure 5.1, u_{Tgreen} represents the *green* resource forecasts, $\overline{U}_i$ the maximum available expected *green* resource for TCA (i), T_i and T_i^* are the indoor temperature and indoor temperature prediction, u_i and u_i^* are the optimal power generated by the MPC controller and the predicted consumption and v_i represents the disturbances.

5.3 MPC formalization

At each time step, each one of the agents must solve his MPC problem. The objectives are: minimize the energy consumption to heating and cooling; minimize the peak power consumption; maintain the zones within a desired temperature range and maintain the used power within the *green* available bounds. Feedback stability is provided by choosing a sufficiently long predictive horizon and proven by results presented in next shapters. Feasibility is achieved by the use of *soft* constraints in the optimization problem formulation as explained in the sequel.

The generic optimization problem to be solved by each agent at each instant, assumes the following form:

$$\begin{aligned} \min_{U,\bar{\varepsilon},\underline{\varepsilon},\bar{\gamma},\underline{\gamma}} J_i(k) = & \sum_{j=0}^{H_p-1}\left[\sum_{l=1}^{Nd_i}\underbrace{u_l^i(k+j)^T\varphi_l^i u_l^i(k+j)}_{Consumption}\right] + \sum_{l=1}^{Nd_i}\underbrace{\phi_i max\left\{{u_l^i}^2(k),\ldots.,{u_l^i}^2(k+H_p-1)\right\}}_{Power\ peaks} \\ & + \sum_{j=1}^{H_p}\left[\sum_{l=1}^{Nd_i}\left(\underbrace{\varepsilon_l^i(k+j)^T\Xi_l^i\varepsilon_l^i(k+j)}_{Comfort\ violation} + \underbrace{\gamma_l^i(k+j)^T\Psi_l^i\gamma_l^i(k+j)}_{Power\ violation}\right)\right], \end{aligned} \tag{5.1}$$

$$\begin{aligned} \min_{U_i,\varepsilon_i,\gamma_i} J_i(k) = & \ \varepsilon_i^T(k)\Xi_i\varepsilon_i(k) + \gamma_i^T(k)\Psi_i\gamma_i(k) + U_i^T(k)R_iU_i(k) \\ & + \sum_{l=1}^{Nd_i}\phi_i max\ \left\{{u_l^i}^2(k),\ldots.,{u_l^i}^2(k+H_p-1)\right\}, \end{aligned} \tag{5.2}$$

with,

$$U_i(k) = \begin{bmatrix} U_i^1(k) \\ U_i^2(k) \\ \vdots \\ U_i^{Nd}(k) \end{bmatrix}, \tag{5.3}$$

$$\varepsilon_i(k) = \begin{bmatrix} \bar{\varepsilon}_i^1(k) \\ \bar{\varepsilon}_i^2(k) \\ \vdots \\ \bar{\varepsilon}_i^{Nd}(k) \\ \underline{\varepsilon}_i^1(k) \\ \underline{\varepsilon}_i^2(k) \\ \vdots \\ \underline{\varepsilon}_i^{Nd}(k) \end{bmatrix}, \bar{\varepsilon}_i^l(k) = \begin{bmatrix} \bar{\varepsilon}_i^l(k+1) \\ \bar{\varepsilon}_i^l(k+2) \\ \vdots \\ \bar{\varepsilon}_i^l(k+H_P) \end{bmatrix}, \underline{\varepsilon}_i^l(k) = \begin{bmatrix} \underline{\varepsilon}_i^l(k+1) \\ \underline{\varepsilon}_i^l(k+2) \\ \vdots \\ \underline{\varepsilon}_i^l(k+H_P) \end{bmatrix}, \tag{5.4}$$

$$\gamma_i(k) = \begin{bmatrix} \bar{\gamma}_i(k) \\ \underline{\gamma}_i(k) \end{bmatrix}, \bar{\gamma}_i(k) = \begin{bmatrix} \bar{\gamma}_i(k+1) \\ \bar{\gamma}_i(k+2) \\ \vdots \\ \bar{\gamma}_i(k+H_P) \end{bmatrix}, \underline{\gamma}_i(k) = \begin{bmatrix} \underline{\gamma}_i(k+1) \\ \underline{\gamma}_i(k+2) \\ \vdots \\ \underline{\gamma}_i(k+H_P) \end{bmatrix}. \tag{5.5}$$

Resulting in quadratic optimization problem in the compact form

$$\min_{Z_i} J_i(k) = Z_i^T \Theta Z_i + \sum_{l=1}^{Nd_i} \phi_{il} max \left\{ {u_l^i}^2(k), \ldots, {u_l^i}^2(k + H_p - 1) \right\}. \tag{5.6}$$

With

$$Z_i = \begin{bmatrix} U_i \\ \varepsilon_i \\ \gamma_i \end{bmatrix}, \Theta = \begin{bmatrix} \varphi_i & 0 & 0 \\ 0 & \Xi_i & 0 \\ 0 & 0 & \Psi_i \end{bmatrix}, \tag{5.7}$$

and subject to the following constraints,

$$x_l^i(k+j+1) = A_{ll}^{ii} x_l^i(k+j) + B_l^i u_l^i(k+j) + \underbrace{\sum_{\substack{g=1 \\ (g \neq l)}}^{Nd_i} \left(A_{lg}^{ii} \tilde{x}_l^i(k+j) \right)}_{\substack{predicted\ temperatures \\ from\ adjacent\ areas \\ inside\ the\ same\ house}} + \underbrace{\sum_{\substack{h=1 \\ (h \neq i)}}^{Ns} \sum_{m=1}^{Nd_h} \left(A_{lm}^{ih} \tilde{x}_m^h(k+j) \right)}_{\substack{predicted\ temperatures \\ from\ adjacent\ areas \\ from\ other\ houses}} \tag{5.8}$$
$$+ v_l^i(k+j),$$
$$, j = 1 \ldots H_P$$

$$\underline{T_l}^i(k+j) - \underline{\varepsilon_l}^i(k+j) \leq x_l^i(k+j) \leq \bar{T}_l^i(k+j) + \bar{\varepsilon}_l^i(k+j), \tag{5.9}$$

$$\underline{U_i}(k+j-1) - \underline{\gamma_i}(k+j-1) \leq \sum_{l=1}^{Nd_i} u_l^i(k+j-1) \leq \bar{U}_i(k+j-1) + \bar{\gamma}_i(k+j-1), \tag{5.10}$$

$$\underline{\gamma_i}, \bar{\gamma}_i, \underline{\varepsilon_l}^i, \bar{\varepsilon}_l^i \geq 0. \tag{5.11}$$

In (5.1) $Nd_i$is the number of divisions of house (*i*), u_i^l represents the power control inputs from house (*i*) division (*l*), $\phi_i$is the penalty on peak power consumption, Ξ_i is the penalty on the comfort constraint violation, $\Psi_i$the penalty on the power constraint violation and H_P is the length of the prediction horizon. In (5.9), $\bar{\varepsilon}_l^i$ and $\underline{\varepsilon_l}^i$ are the vectors of temperature violations that are above and below the desired comfort zone defined by $\bar{T}_l^i$ and $\underline{T_l}^i$. In (5.10), the coupled power constraint, $\bar{\gamma}_i$ and $\underline{\gamma_i}$are the power violations that are above or lower the maximum,$\bar{U}_i$, and minimum, $\underline{U_i}$, available *green* power for heating/cooling the house, with $\underline{U_i} = -\bar{U}_i$. Remark that, in each TCA (*i*), the power sum in all divisions cannot exceed $\bar{U}_i$ and that in (5.8) ${x_l^i}^*$and ${u_l^i}^*$represent the predicted temperature and power consumption within the prediction horizon.

With this approach each TCA can have different hourly penalties, allowing the consumer to choose between more/less comfort and cost during the day as Figure 5.2 exemplify. This procedure was implemented in Algorithm II.

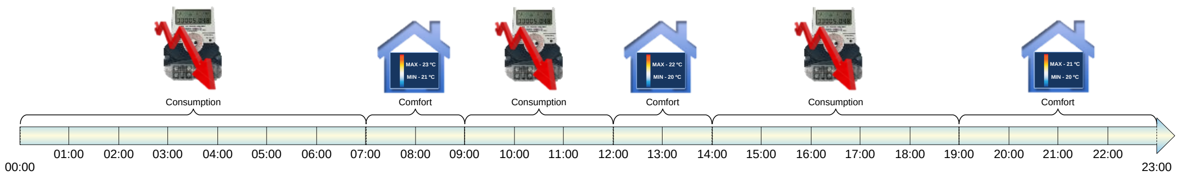

Figure 5.2. Daily consumer profile.

An example of formulization is made for and distributed situation where two distinct TCA's are dynamically and constraints coupled.

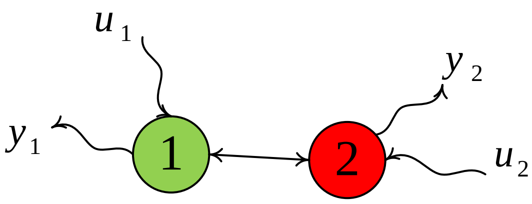

Figure 5.3. Thermally coupled TCA's.

For TCA1 and TCA2 it can be written

$$\begin{cases} C_{1_{eq}}^{1}\dot{T}_1^1 = u_1^1 + \dfrac{T_{oa} - T_1^1}{R_{1_{eq}}^1} + \dfrac{T_1^2 - T_1^1}{R_{11_{eq}}^{12}} + P_{1_{Pd}}^1, \\ C_{1_{eq}}^{2}\dot{T}_1^2 = u_1^2 + \dfrac{T_{oa} - T_1^2}{R_{1_{eq}}^2} + \dfrac{T_1^1 - T_1^2}{R_{11_{eq}}^{12}} + P_{1_{Pd}}^2 \end{cases} \tag{5.12}$$

$$\begin{cases} C_{1_{eq}}^{1}\dot{T}_1^1 = u_1^1 - \left(\dfrac{1}{R_{1_{eq}}^1} + \dfrac{1}{R_{11_{eq}}^{12}}\right)T_1^1 + \dfrac{T_{oa} - T_1^1}{R_{1_{eq}}^1} + \dfrac{T_1^2}{R_{11_{eq}}^{12}} + \dfrac{T_{oa}}{R_{1_{eq}}^1} + P_{1_{Pd}}^1 \\ C_{1_{eq}}^{2}\dot{T}_1^2 = u_1^2 - \left(\dfrac{1}{R_{1_{eq}}^2} + \dfrac{1}{R_{11_{eq}}^{12}}\right)T_1^2 + \dfrac{T_{oa} - T_1^2}{R_{1_{eq}}^2} + \dfrac{T_1^1}{R_{11_{eq}}^{12}} + \dfrac{T_{oa}}{R_{1_{eq}}^2} + P_{1_{Pd}}^2 \end{cases} \tag{5.13}$$

$$\begin{bmatrix} \dot{T}_1^1 \\ \dot{T}_1^2 \end{bmatrix} = \begin{bmatrix} -\dfrac{R_{1_{eq}}^1 + R_{11_{eq}}^{12}}{R_{1_{eq}}^1 C_{1_{eq}}^1 R_{11_{eq}}^{12}} & \dfrac{1}{C_{1_{eq}}^1 R_{11_{eq}}^{12}} \\ \dfrac{1}{C_{1_{eq}}^2 R_{11_{eq}}^{12}} & -\dfrac{R_{1_{eq}}^2 + R_{11_{eq}}^{12}}{R_{1_{eq}}^2 C_{1_{eq}}^2 R_{11_{eq}}^{12}} \end{bmatrix} \begin{bmatrix} T_1^1 \\ T_1^2 \end{bmatrix} + \begin{bmatrix} \dfrac{1}{C_{1_{eq}}^1} & 0 \\ 0 & \dfrac{1}{C_{1_{eq}}^2} \end{bmatrix} \begin{bmatrix} u_1^1 \\ u_1^2 \end{bmatrix} + \begin{bmatrix} \dfrac{T_{oa}}{C_{1_{eq}}^1 R_{1_{eq}}^1} + \dfrac{P_{1_{Pd}}^1}{C_{1_{eq}}^1} \\ \dfrac{T_{oa}}{C_{1_{eq}}^2 R_{1_{eq}}^2} + \dfrac{P_{1_{Pd}}^2}{C_{1_{eq}}^2} \end{bmatrix}. \tag{5.14}$$

For TCA 1 the plant model representation (5.14) can be rewritten and changed into a discrete model using Euler discretization with a sampling time of Δt.

$$\dot{T}_1^1 = \frac{T(k+1) - T(k)}{\Delta t}, \tag{5.15}$$

$$\frac{T(k+1)-T(k)}{\Delta t} = -\frac{R_{1_{eq}}^{1}+R_{11_{eq}}^{12}}{R_{1_{eq}}^{1}C_{1_{eq}}^{1}R_{11_{eq}}^{12}}\dot{T}_1^1(k) - \frac{1}{C_{1_{eq}}^{1}R_{11_{eq}}^{12}}T_1^2(k) + \frac{1}{C_{1_{eq}}^{1}}u_1^1(k) + \frac{1}{C_{1_{eq}}^{1}R_{1_{eq}}^{1}}T_{oa}(k) + \frac{1}{C_{1_{eq}}^{1}}P_{1_{Pd}}^{1}(k), \tag{5.16}$$

$$T_1^1(k+1) = A_{11}^{11}T_1^1(k) + B_1^1u_1^1(k) + A_{11}^{12}T_1^2(k) + v_1^1(k), \tag{5.17}$$

where

$$A_1 = A_{11}^{11} = \left(1 - \frac{R_{1_{eq}}^{1}+R_{11_{eq}}^{12}}{C_{1_{eq}}^{1}R_{1_{eq}}^{1}R_{11_{eq}}^{12}}\Delta t\right), \tag{5.18}$$

$$D_1 = v_1^1 = \frac{P_{1_{Pd}}^{1}}{C_{1_{eq}}^{1}}\Delta \mathrm{t} + \frac{\mathrm{T_{oa}}}{R_{1_{eq}}^{1}C_{1_{eq}}^{1}}\Delta \mathrm{t},$$

$$B_1 = B_1^1 = \frac{1}{C_{1_{eq}}^{1}}\Delta t,$$

$$C_1 = A_{11}^{12} = \frac{1}{R_{11_{eq}}^{12}C_{1_{eq}}^{1}}\Delta \mathrm{t}.$$

For several instants, (5.17) can be written as follows,

$$T_1^1(1) = A_1T_1^1(0) + B_1u_1^1(0) + C_1T_1^2(0) + D_1(0), \tag{5.19}$$

$$T_1^1(2) = (A_1)^2T_1^1(0) + A_1B_1u_1^1(0) + A_1C_1T_1^2(0) + A_1D_1(0) + B_1u_1^1(1) + C_1T_1^2(1) + D_1(1), \tag{5.20}$$

$$T_1^1(3) = (A_1)^3T_1^1(0) + (A_1)^2B_1u_1^1(0) + (A_1)^2C_1T_1^2(0) + (A_1)^2D_1(0) + A_1B_1u_1^1(1) + A_1C_1T_1^2(1) + A_1D_1(1) + B_1u_1^1(2) + C_1T_1^2(2) + D_1(2), \tag{5.21}$$

Therefore,

$$MatU = \begin{bmatrix} B_1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1B_1 & B_1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2B_1 & A_1B & B_1 & \ddots & \cdots & \vdots \\ {A_1}^3B_1 & {A_1}^2B_1 & A_1B_1 & B_1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & B_1 & 0 \\ {A_1}^{H_P}B_1 & {A_1}^{H_P-1}B_1 & \cdots & \cdots & A_1B_1 & B_1 \end{bmatrix}, \tag{5.22}$$

$$MatT_x = \begin{bmatrix} C_1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1C_1 & C_1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2C_1 & A_1C_1 & C_1 & \ddots & \cdots & \vdots \\ {A_1}^3C_1 & {A_1}^2C_1 & A_1C_1 & C_1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & C_1 & 0 \\ {A_1}^{H_P}C_1 & {A_1}^{H_P-1}C_1 & \cdots & \cdots & A_1C_1 & C_1 \end{bmatrix}, \tag{5.23}$$

$$MatD = \begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1 & 1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2 & A_1 & 1 & \ddots & \cdots & \vdots \\ {A_1}^3 & {A_1}^2 & A_1 & 1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & 1 & 0 \\ {A_1}^{H_P} & {A_1}^{H_P-1} & \cdots & \cdots & A_1 & 1 \end{bmatrix}, \tag{5.24}$$

$$MatT = [A_1 \quad {A_1}^2 \quad {A_1}^3 \quad \cdots \quad {A_1}^{H_P}]. \tag{5.25}$$

It is considered that the constraints (5.9) and (5.10) must assume the form of $Ax<B$ with,

$$x = \left[u_1^1; \underline{\varepsilon}_1; \bar{\varepsilon}_1; \underline{\gamma}_1; \bar{\gamma}_1\right]^T, \tag{5.26}$$

where, $\underline{\varepsilon}_1$ and $\bar{\varepsilon}_1$ are the vectors of temperature violations that are above and below the desired comfort zone defined by $\underline{T}_1^1$ and $\overline{T}_1^1$, and $\overline{\gamma}_1$ and $\underline{\gamma}_1$ are the power violations that are above or lower the maximum.

Temperature constraints: $T_1^1(k+1) = A_1T_1^1(k) + B_1u_1^1(k) + C_1T_1^2(k) + D_1(k)$,

$$\underline{T}_1^1 - \underline{\varepsilon}_1 \leq T_1^1 \leq \overline{T}_1^1, + \bar{\varepsilon}_1, \tag{5.27}$$

$$\underline{T}_1^1 - \begin{bmatrix} \underline{\varepsilon}_1(1) \\ \underline{\varepsilon}_1(2) \\ \vdots \\ \vdots \\ \vdots \\ \underline{\varepsilon}_1(H_P) \end{bmatrix} \leq \begin{bmatrix} A_1 \\ {A_1}^2 \\ {A_1}^3 \\ \vdots \\ \vdots \\ {A_1}^{H_P} \end{bmatrix} T_1^1(0) \begin{bmatrix} B_1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1B_1 & B_1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2B_1 & A_1B & B_1 & \ddots & \cdots & \vdots \\ {A_1}^3B_1 & {A_1}^2B_1 & A_1B_1 & B_1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & B_1 & 0 \\ {A_1}^{H_P}B_1 & {A_1}^{H_P-1}B_1 & \cdots & \cdots & A_1B_1 & B_1 \end{bmatrix} \begin{bmatrix} u_1^1(0) \\ u_1^1(1) \\ \vdots \\ \vdots \\ \vdots \\ u_1^1(H_P-1) \end{bmatrix} + \tag{5.28}$$

$$\begin{bmatrix} C_1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1C_1 & C_1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2C_1 & A_1C_1 & C_1 & \ddots & \cdots & \vdots \\ {A_1}^3C_1 & {A_1}^2C_1 & A_1C_1 & C_1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & C_1 & 0 \\ {A_1}^{H_P}C_1 & {A_1}^{H_P-1}C_1 & \cdots & \cdots & A_1C_1 & C_1 \end{bmatrix} \begin{bmatrix} T_1^2(0) \\ T_1^2(1) \\ \vdots \\ \vdots \\ \vdots \\ T_1^2(H_P-1) \end{bmatrix} +$$

$$\begin{bmatrix} 1 & 0 & \cdots & \cdots & \cdots & 0 \\ A_1 & 1 & \ddots & \cdots & \cdots & \vdots \\ {A_1}^2 & A_1 & 1 & \ddots & \cdots & \vdots \\ {A_1}^3 & {A_1}^2 & A_1 & 1 & \ddots & \vdots \\ \vdots & \vdots & \vdots & \vdots & 1 & 0 \\ {A_1}^{H_P} & {A_1}^{H_P-1} & \cdots & \cdots & A_1 & 1 \end{bmatrix} \begin{bmatrix} D_1(0) \\ D_1(1) \\ \vdots \\ \vdots \\ \vdots \\ D_1(H_P-1) \end{bmatrix} \leq \overline{T}_1^1, + \begin{bmatrix} \bar{\varepsilon}_1(1) \\ \bar{\varepsilon}_1(2) \\ \vdots \\ \vdots \\ \vdots \\ \bar{\varepsilon}_1(H_P) \end{bmatrix}.$$

Lower temperature constraint bound

$$\underline{T}_1^1 - \underline{\varepsilon}_1 \leq T_1^1, \tag{5.29}$$

$$\underline{T}_1^1 - \underline{\varepsilon}_1 \leq MatT \times T_1^1 + MatU \times u_1^1 + MatT_x \times T_1^2 + MatD \times D_1, \tag{5.30}$$

$$-\Big(\underbrace{\underline{\varepsilon} + MatU \times u_1^1}_{A1}\Big) \leq -\Big(\underbrace{\underline{T}_1^1 - MatT \times T_1^1 + MatT_x \times T_1^2 + MatD \times D_1}_{B1}\Big), \tag{5.31}$$

$$A1 = \left[MatU_{Hp\times Hp} \;\; I_{Hp\times Hp} \;\; 0_{Hp\times Hp} \;\; 0_{Hp\times Hp} \;\; 0_{Hp\times Hp}\right]. \tag{5.32}$$

Similarly, for the upper temperature bound can be written

$$T_1^1 \leq \overline{T}_1^1 + \bar{\varepsilon}_1, \tag{5.33}$$

$$MatT \times T_1^1 + MatU \times u_1^1 + MatT_x \times T_1^2 + MatD \times D_1 \leq \overline{T}_1^1 + \bar{\varepsilon}_1, \tag{5.34}$$

$$\Big(\underbrace{\bar{\varepsilon}_1 + MatU \times u_1^1}_{A2}\Big) \leq -\Big(\underbrace{\overline{T}_1^1 + MatT \times T_1^1 + MatT_x \times T_1^2 + MatD \times D_1}_{B2}\Big), \tag{5.35}$$

$$A2 = \left[MatU_{Hp\times Hp} \;\; 0_{Hp\times Hp} \;\; -I_{Hp\times Hp} \;\; 0_{Hp\times Hp} \;\; 0_{Hp\times Hp}\right]. \tag{5.36}$$

Power constraints also assume the form *Ax<B,* so to the lower bound,

$$\underline{U}_1 - \underline{\gamma}_1 \leq U_1, \tag{5.37}$$

$$\underbrace{-\underline{\gamma}_1 - U_1}_{A3} \leq \underbrace{-\underline{U}_1}_{B3}, \tag{5.38}$$

$$A3 = \left[-I_{Hp\times Hp} \;\; 0_{Hp\times Hp} \;\; 0_{Hp\times Hp} - I_{Hp\times Hp} \;\; 0_{Hp\times Hp}\right]. \tag{5.39}$$

Upper power constraint bound

$$U_1 \leq \overline{U}_1 + \bar{\gamma}_1, \tag{5.40}$$

$$\underbrace{U_1 - \bar{\gamma}_1}_{A4} \leq \underbrace{\overline{U}_1}_{B4}, \tag{5.41}$$

$$\mathrm{A4} = \left[I_{H_p\times H_p} \;\; 0_{H_p\times H_p} \;\; 0_{H_p\times H_p} \;\; 0_{H_p\times H_p} \;\; -I_{H_p\times H_p}\right]. \tag{5.42}$$

Finally for all *soft* constrains in the form of *Ax<B* results in,

$$\begin{bmatrix} -\mathrm{A1} \\ \mathrm{A2} \\ \mathrm{A3} \\ \mathrm{A4} \end{bmatrix} \left[u_1^1; \underline{\varepsilon}_1; \bar{\varepsilon}_1; \underline{\gamma}_1; \bar{\gamma}_1\right]^T = \begin{bmatrix} -B1^T \\ B2^T \\ B3^T \\ B4^T \end{bmatrix}. \tag{5.43}$$

5.3.1 Algorithm I - Implemented sequential scheme

After the methodology description, the algorithm is described. As mentioned it is considered that the sequence order was already stablished by a previous auction. The hourly access sequence is storage in $A_O(N_S \times H_P)$. Remark that, only the divisions that thermally interact pass to each other the information about future indoor temperatures prevision.

Algorithm I - DSM-DMPC Implemented sequential scheme

Required for all TCA's: Thermal disturbances, comfort temperature gap, hourly constraints parameters and auction bid.

For all TCA's W_i initialize:

B_V bid value inside the H_P $(1 \times H_P)$

for k=1 **to** N_C

for i=1 **to** N_S(the number of TCA's)

Apply to all TCA $u_l^i\ (k-1{:}\,k-1+H_P)$ from k-1 instant to obtain $T_l^i(k{:}\,k+H_P)$

Communicate temperature predictions to adjacent TCA's

Update available *green* resource

Calculate the optimal control sequence u_l^i(1:H$_P$) solving OP_i (5.1)-(5.11) with power constraints (5.10) given by $\underline{U_i}$ and $\overline{U}_i$

Update available *green* resource values for next TCA

$$\overline{U}_{i+1}(k{:}\,k+H_P) = \overline{U}_i(k{:}\,k+H_P) - \sum_{l=1}^{Nd_i} u_l^i(k{:}\,k+H_P)$$

end for

end for

Remark: generically, $X(k{:}\,k+H_P)$ represents a line vector $(1 \times H_P)$ containing values from $x(k)$ to $x(k+H_P)$, and $Y(p,k{:}\,k+H_P)$, represents the line p of a matrix $(P \times H_P)$ containing values from y(p,k) to y$(p,k+H_P)$.

Chapter 6

DMPC for Thermal House Comfort with Sequential Access Auction

6.1 Introduction

This chapter presents, in a model predictive control multi-agent systems context, an integrative methodology to manage energy networks from the demand side with strong presence of intermittent energy sources and with energy storage in house-hold or car batteries. In particular is presented a distributed model predictive control solution for indoor comfort that simultaneously optimizes the usage of a limited shared energy resource via a demand side management perspective (Barata et al., 2012b). The control is applied individually to a set of Thermal Control Areas, demand units, where the objective is to minimize the energy cost while maintaining the indoor temperature inside a comfort zone, without exceeding the limited and shared energy resource. The Thermal Control Areas are generally thermodynamically connected in the distributed environment and also are coupled by energy related constraints. The overall system predicts indoor environmental conditions in buildings with different plans which are modelled using an electro-thermal modular scheme (Chapter 3.4). For control purposes, this modular scheme allows an easy modelling of buildings with different plans where adjacent areas can thermally interact.

The results are presented with two different approaches. In Chapter 6.2, the energy split performance is based on a fixed sequential order, established from a previously done auction wherein the bids are made by each Thermal Control Area, acting as demand side management agents and based on the energy daily price. In Chapter 6.3, bids can be made in accordance to the consumption needs. Each TCA has an hourly known consumption profile and the bid value is directly related to that consumption behaviour. Thus, to the assumptions made in Chaper 5.2 the next dots are added, stipulating the incremented specificities made in this chapter:

- *Green* resource which is not consumed at the final of a certain instant is stored in batteries up to capacity value (*BcV*). When *BcV* is reached it is considered that the remaining *green* resource is delivered to the grid;
- The access order to *green* resource varies hourly;
- Each TCA has a known fixed 24 hours consumption profile, $Cw_l^i(k\colon k + H_P)$ and it is established a priority level from 1 (low) to 3 (high) for each hour indicating how important it is to have available resource to supply the load;
- The bid value of each house is made in accordance with the chosen priority level, the hours with higher priority levels indicate high consumption and consequently a higher bid value;
- The access to *green* resource is done hourly in accordance with the made bid value. The one that is able to pay more uses the needed stock first and the second can use only the remaining energy, and so on.
- The cost function penalty values may hourly vary;

The developed solutions are explained by Algorithm II and are applied to different scenarios wherein the results illustrate the benefits of the proposed approach.

6.2 Access order with fixed stablished sequence

To explain and prove the concept, simulation results were made in accordance with the scheme presented in Figure 6.2.

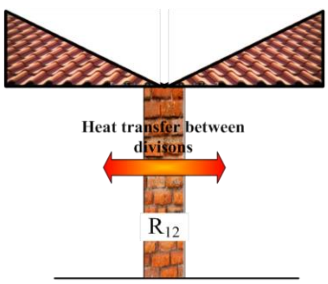

Figure 6.1: Heat transfer between divisions example.

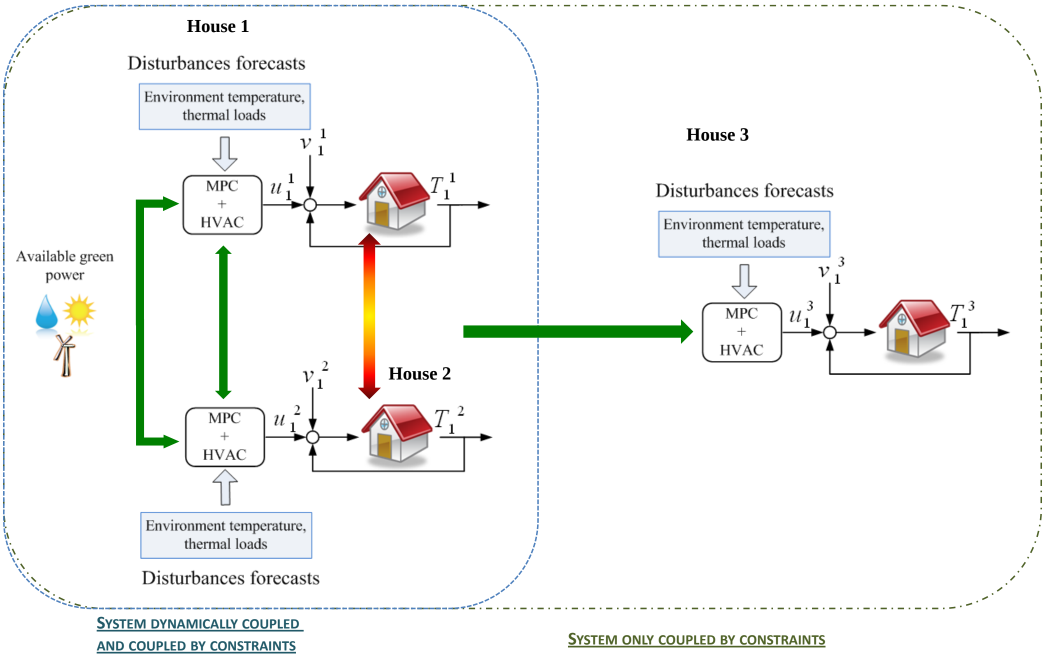

Figure 6.2: System implementation scheme block diagram.

Three houses are considered, two of them thermally interacting (with a thermal resistance between them of R_{12}=30ºC/kW as shown in Figure 6.1 and the third is isolated.

6.2.1 Results

It is considered that all TCA´s have the same outdoor temperature presented in Figure 6.3.

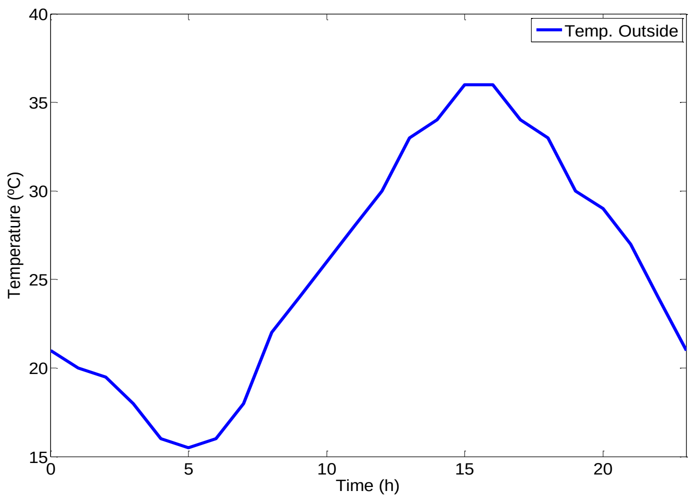

Figure 6.3. Outdoor temperature forecasting.

The thermal characteristics and prices for all agents and scenarios are presented in Table 6.1.

Table 6.1. Distributed parameters

Parameter	A_1	A_2	A_3	Units
R_{eq}	50	50	75	ºC/kW
C_{eq}	9.2×10^3	9.2×10^3	9.2×10^3	kJ/ºC
Green Price (per kWh)	0.09	0.08	0.07	€
Red Price(per kWh)		0.18		€

As mentioned, agents can also have distinct penalties on power and temperature constraints violations, they can hourly privilege comfort or cost according to consumer choice. Therefore, to explore the concept several scenarios are here presented.

6.2.1.1 Scenario I - Balanced parameterization

The first, it is considered a balanced scenario, with no energy storage and no explicit preference between comfort or consumption. Table 6.2 shows the penalty values that are used in the first scenario.

Table 6.2. Scenario I - Penalty values

Parameter	A_1	A_2	A_3
Ξ	50	50	50
ψ	100	100	30
ϕ	2	2	2
φ	1	1	1

The thermal disturbances forecasts and the indoor temperature with its constraints for the TCA, A_1, A_2 and A_3 have the profile presented in Figure 6.4, Figure 6.5 and Figure 6.6 respectively.

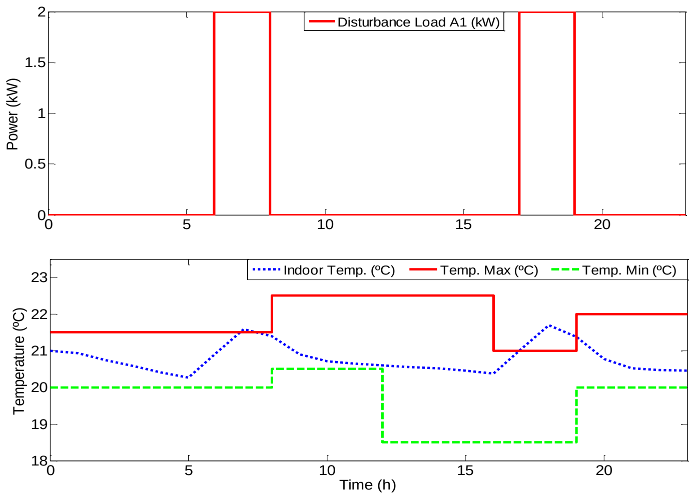

Figure 6.4. Scenario I - Disturbance forecasting and indoor temperature A_1.

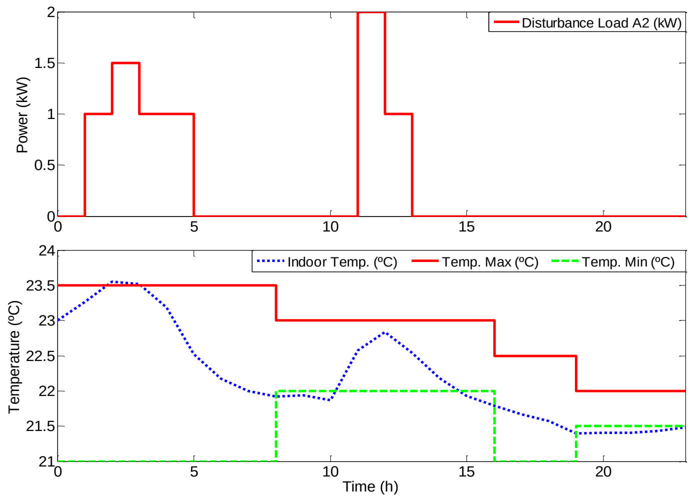

Figure 6.5. Scenario I - Disturbance forecasting and indoor temperature A_2.

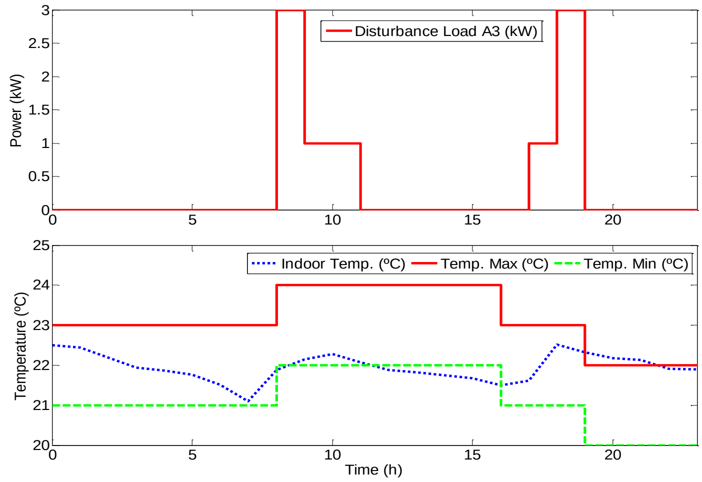

Figure 6.6. Scenario I - Disturbance forecasting and indoor temperature A_3.

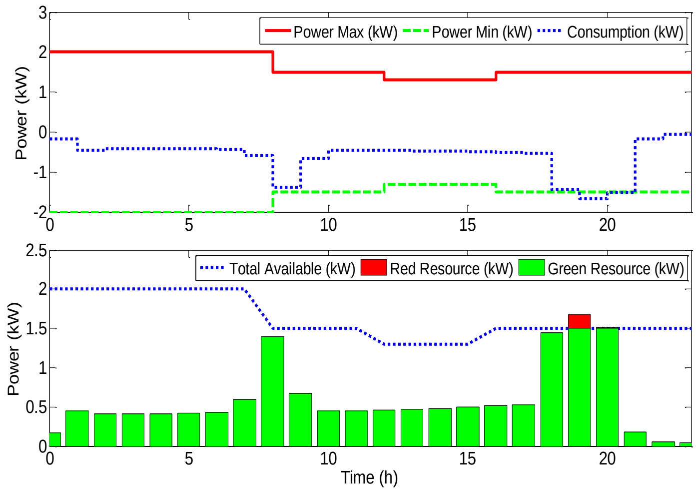

Figure 6.7. Scenario I - A_1 power profile.

Despite the thermal disturbances, it can be seen in that the indoor temperatures are predominantly inside their narrow bounds. The Figure 6.7, Figure 6.8 and Figure 6.9 show, for TCA, A_1, A_2 and A_3 respectively, the used power to acclimatize the spaces and the available *green* resource to do it. The figures also show the amount and the type of the consumed power.

Figure 6.8. Scenario I - A_2 power profile.

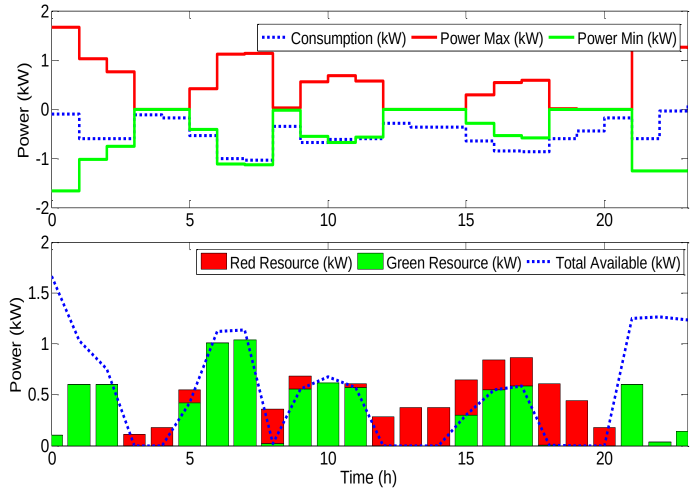

Figure 6.9. Scenario I - A_3 power profile.

The power consumption behaviour shows that the controllers try to consume only when the *green* resource is available. The compromise between comfort and consumption is notorious, the controllers are always attempting to accomplish both constraints, but when is not possible it compensates with one inside range and the other outside.

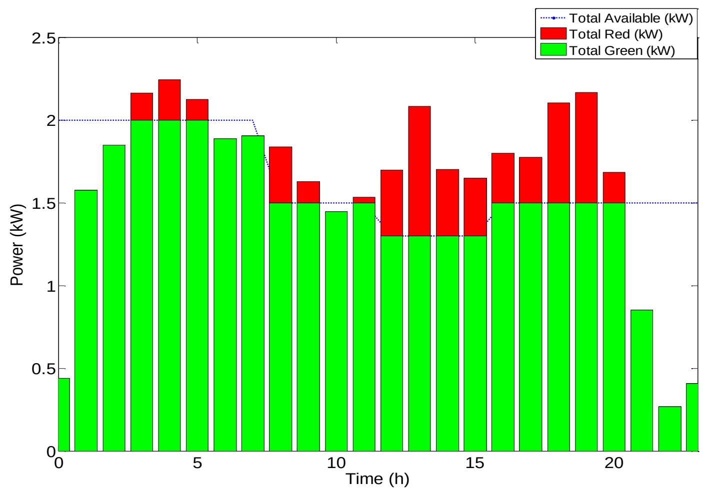

Figure 6.10. Scenario I - Global consumption characterization.

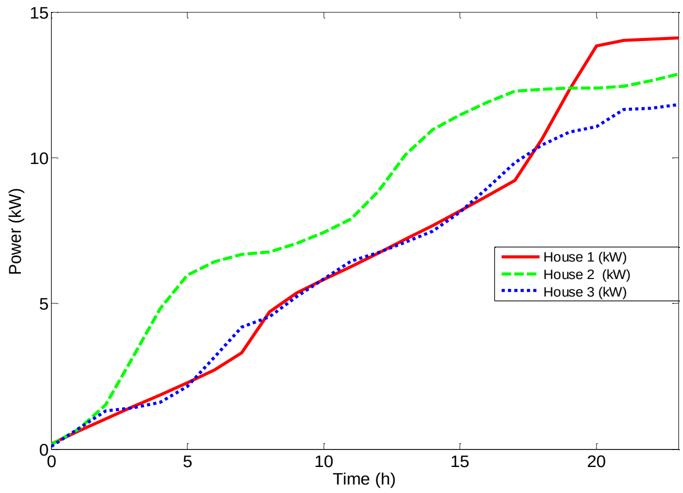

Figure 6.11. Scenario I - Power profile.

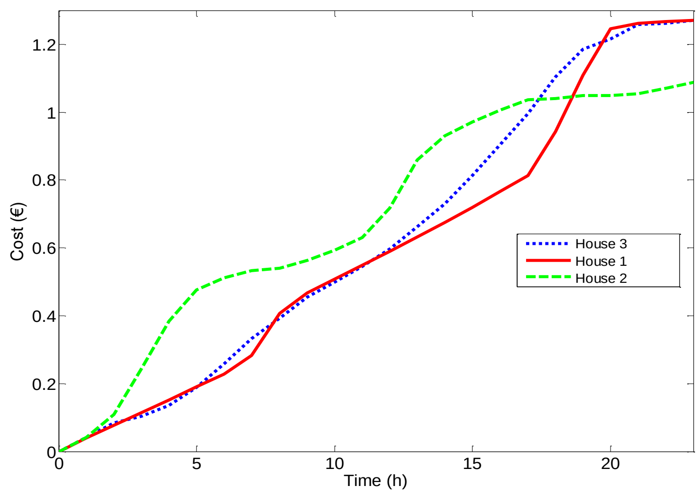

Figure 6.12. Scenario I - Heating/cooling total cost.

Being the last in the sequence, A_3 receives merely the remainder resource, which in several periods is null obliging to a major consumption of *red* resource. Due this situation, despite A_3 having the lowest consumption, Figure 6.11, is the one that have the highest cost Figure 6.12.

6.2.1.2 Scenario II - Balanced parameterization with storage

The second scenario intends to show the benefit of having energy storage, been the only difference with Scenario I the increment of a set of batteries with 1.5 kWh of capacity, Figure 6.22. The thermal disturbances forecasts and the indoor temperature with its constraints for the TCA, A_1, A_2 and A_3 in this Scenario II, have the profile presented in Figure 6.13, Figure 6.14 and Figure 6.15 respectively.

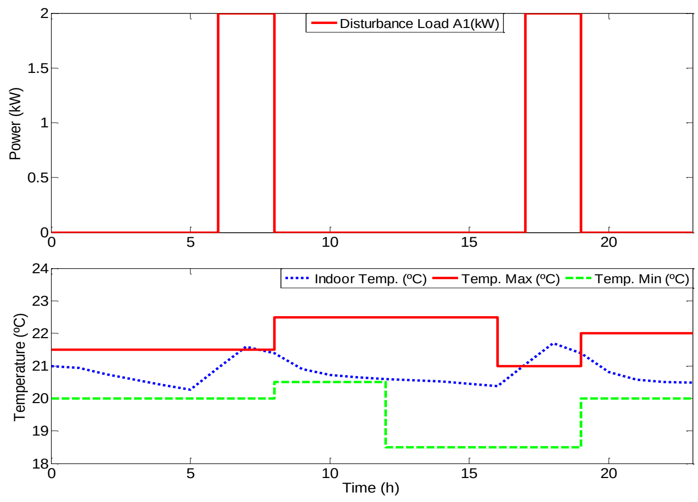

Figure 6.13. Scenario II - Disturbance forecasting and indoor temperature A_1.

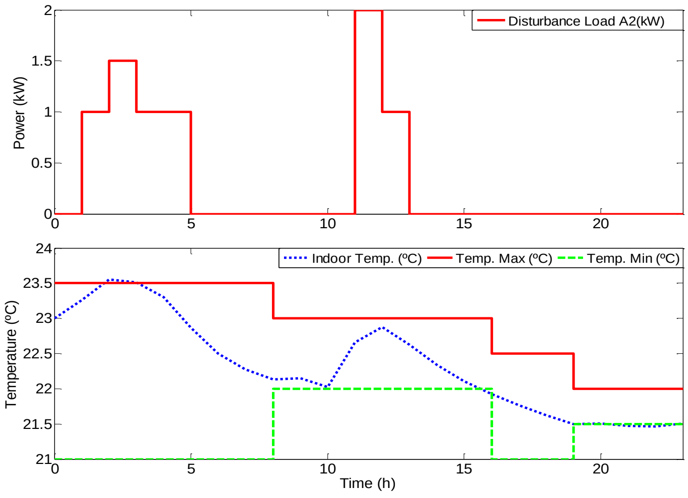

Figure 6.14. Scenario II - Disturbance forecasting and indoor temperature A_2.

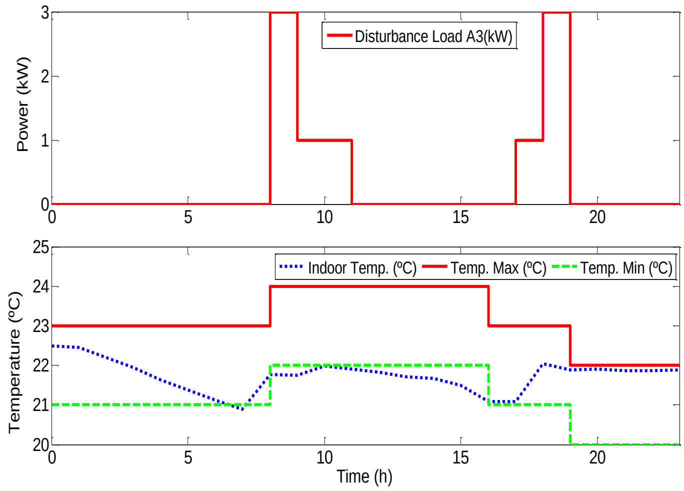

Figure 6.15. Scenario II - Disturbance forecasting and indoor temperature A_3.

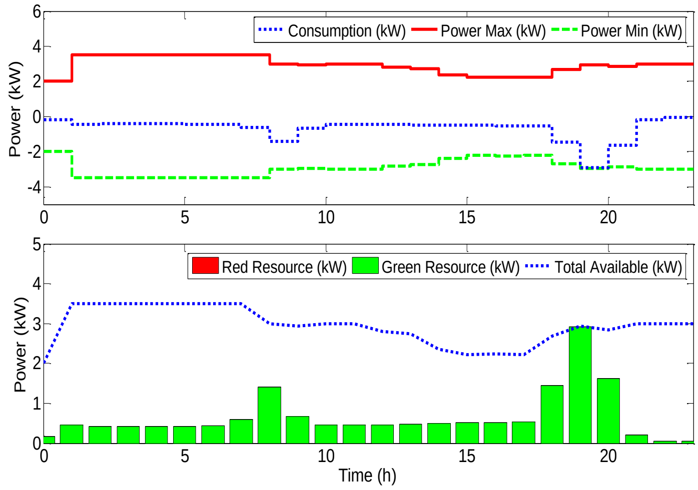

Figure 6.16. Scenario II – A_1 power profile.

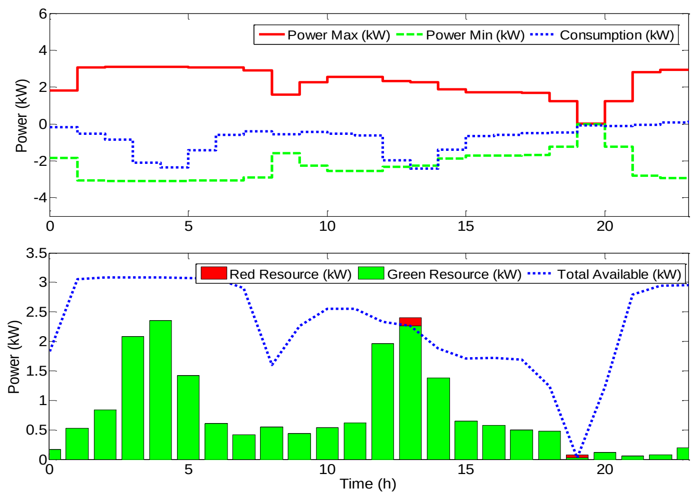

Figure 6.17. Scenario II – A_2 power profile.

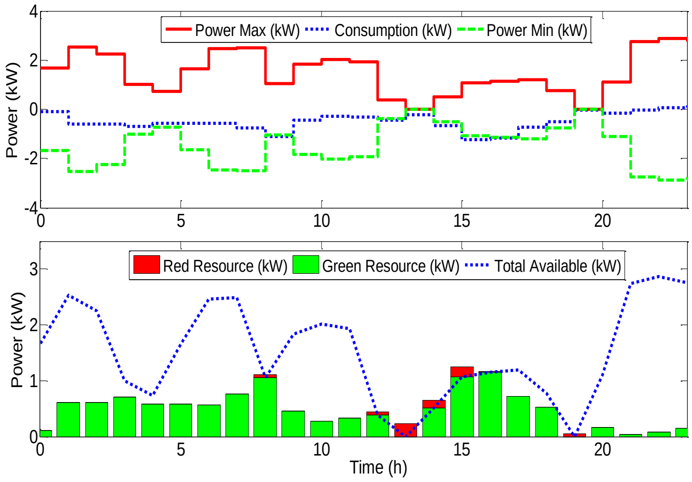

Figure 6.18. Scenario II – A_3 power profile.

Despite the thermal disturbances, it can be seen in that the indoor temperatures are predominantly inside their narrow bounds.

As expected, with this energy supplement the power constraint of all TCA's was respected, exceptionally in the interval between 12-15h in A_3, where a small amount of red resource was consumed.

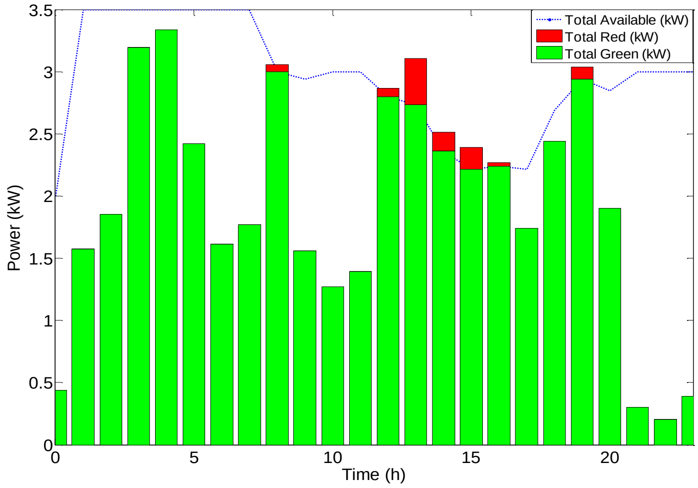

Figure 6.19. Scenario II - Global consumption characterization.

Comparatively with Figure 6.10, Figure 6.19 shows that the *red* resource consumption was significantly reduced. The agent that most benefit with this modification was A_3, the energy surplus allows it to consume almost exclusively *green* resource bought at lower bid price , and thus, is the one that presents lesser costs, Figure 6.21.

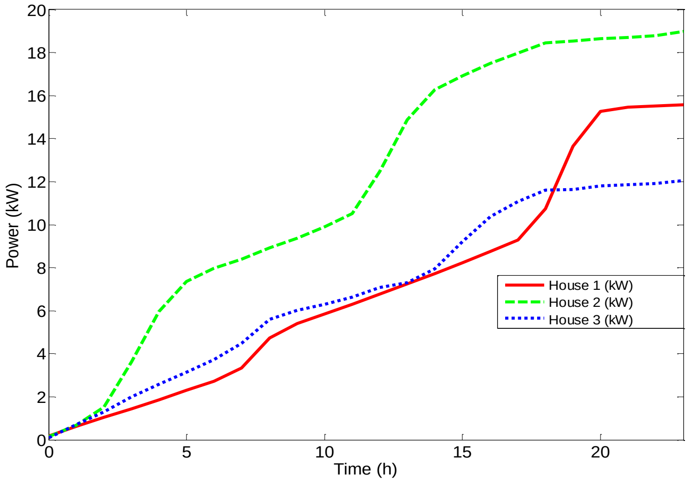

Figure 6.20. Scenario II - Power profile.

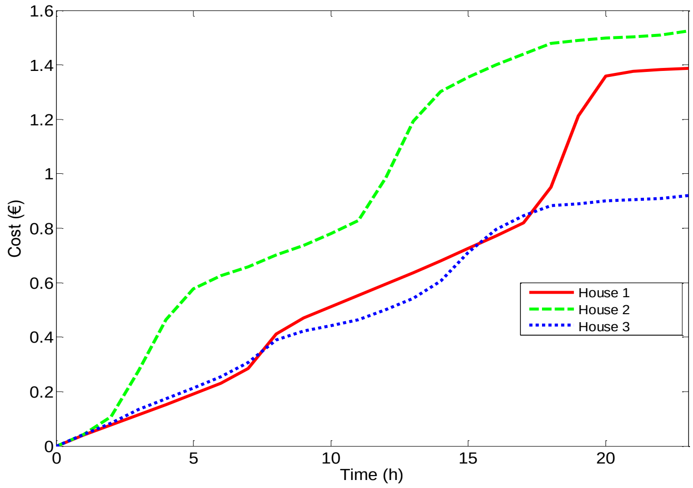

Figure 6.21. Scenario II - Heating/cooling total cost.

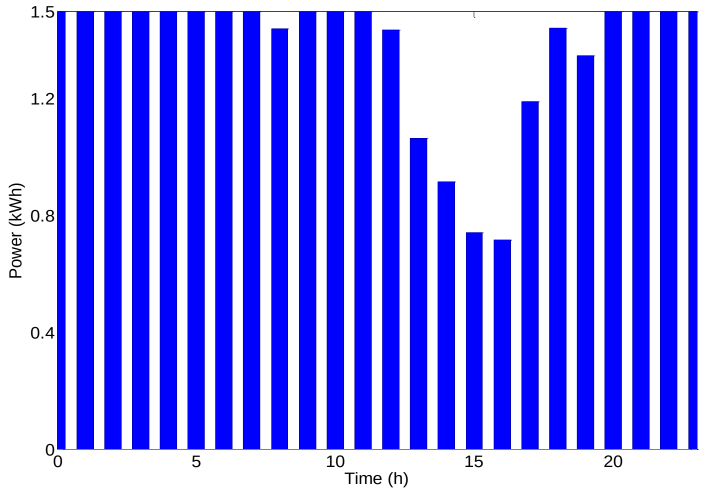

Figure 6.22. Scenario II - Batteries profile.

6.2.1.3 Scenario III - Parameterization for cost benefits

In the third scenario the penalty values of the parameters related with consumption were increased. The comfort issues are now less important, with the agents mainly concerned with lower consumptions and in satisfy the power constraint. With this variation, the *soft* power constraint was transformed in a *hard* constraint.

Table 6.3. Scenario III - Penalty values

Parameter	A_1	A_2	A_3
Ξ	50	50	50
ψ	100000	100000	30000
ϕ	20	20	20
φ	10	10	10

Due the scarcity of *green* resource and the obligation to respect the power limits, A_3 was the one that presented lower consumptions, Figure 6.30, and consequently minor costs, but on the other hand, the indoor temperature was the most penalized with the highest deviation from the chosen comfort range. With this parameterization, the consumption profile always maintained inside bounds, for all TCA's, Figure 6.26, Figure 6.27 and Figure 6.28. Consequently, in Figure 6.29 can be seen that any or negligible *red* resource was consumed.

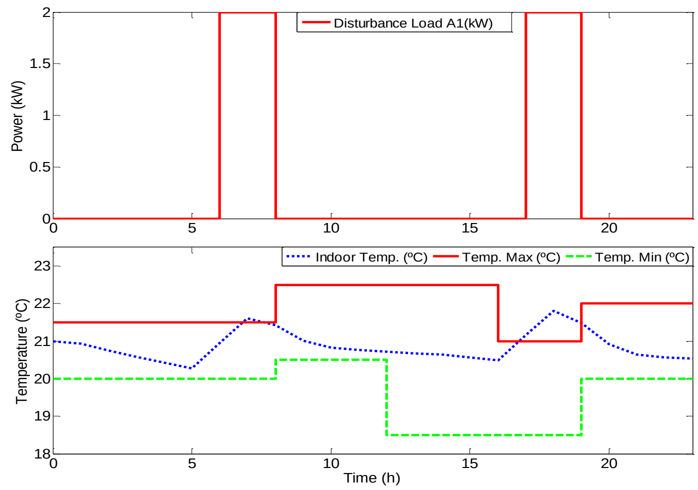

Figure 6.23. Scenario III - Disturbance forecasting and indoor temperature A_1.

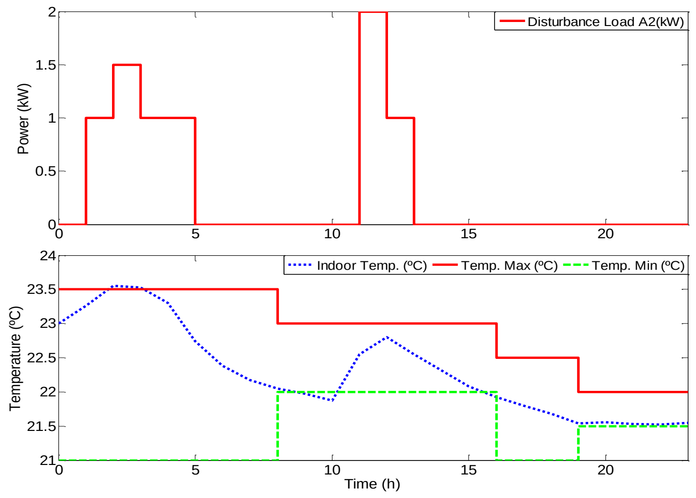

Figure 6.24. Scenario III - Disturbance forecasting and indoor temperature A_2.

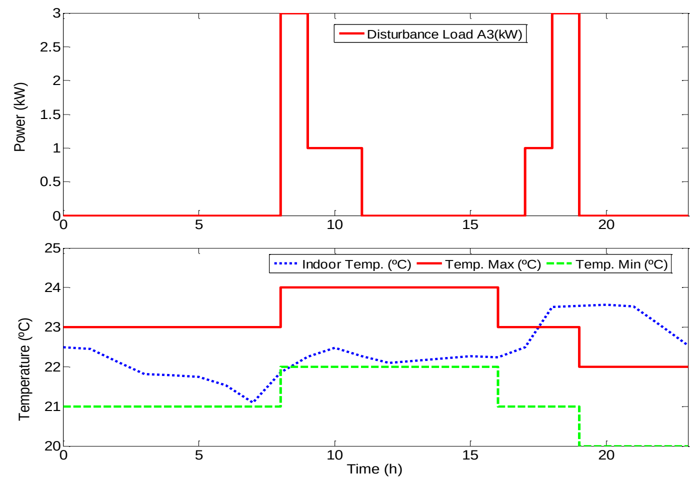

Figure 6.25. Scenario III - Disturbance forecasting and indoor temperature A_3.

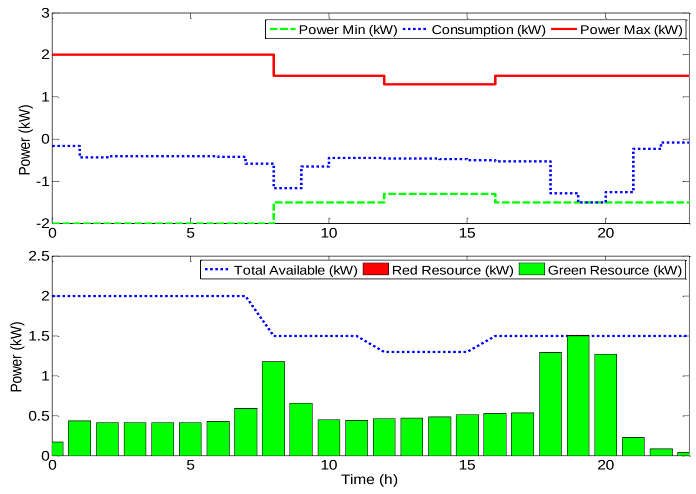

Figure 6.26. Scenario III – A_1 power profile.

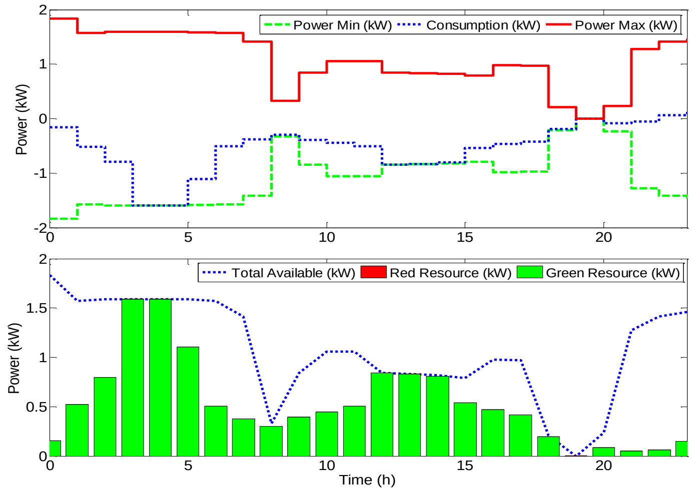

Figure 6.27. Scenario III – A_2 power profile.

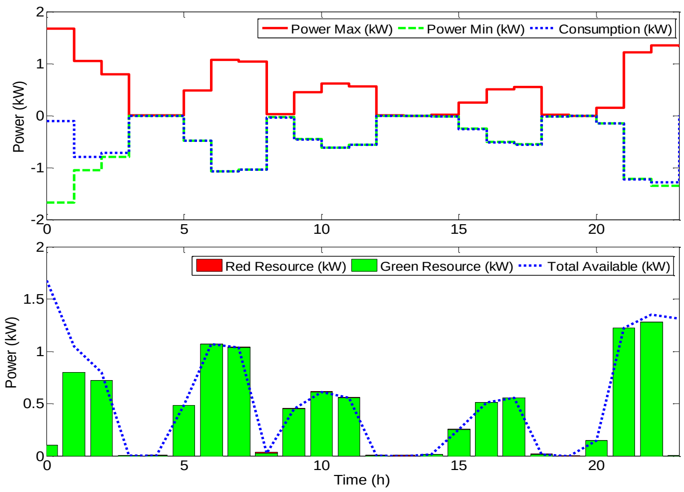

Figure 6.28. Scenario III – A_3 power profile.

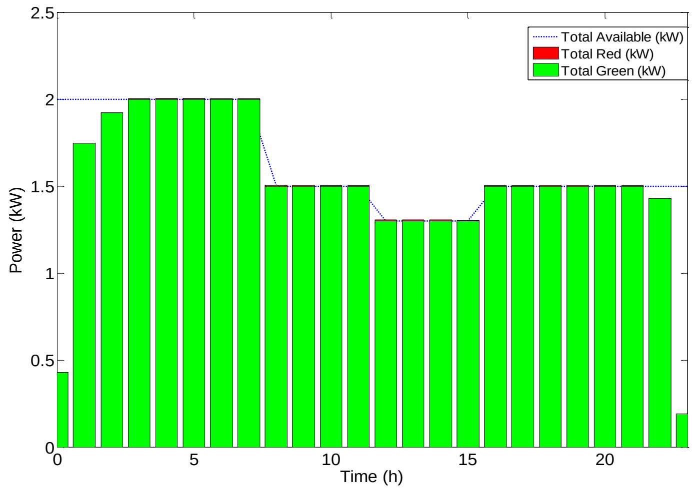

Figure 6.29. Scenario III - Global consumption characterization.

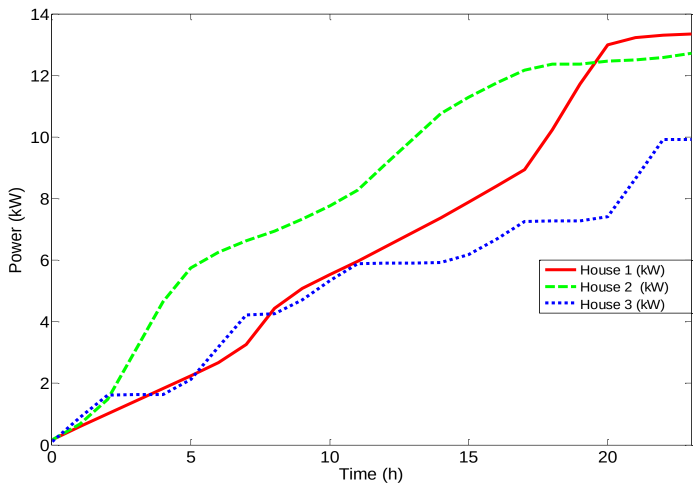

Figure 6.30. Scenario III - Power profile.

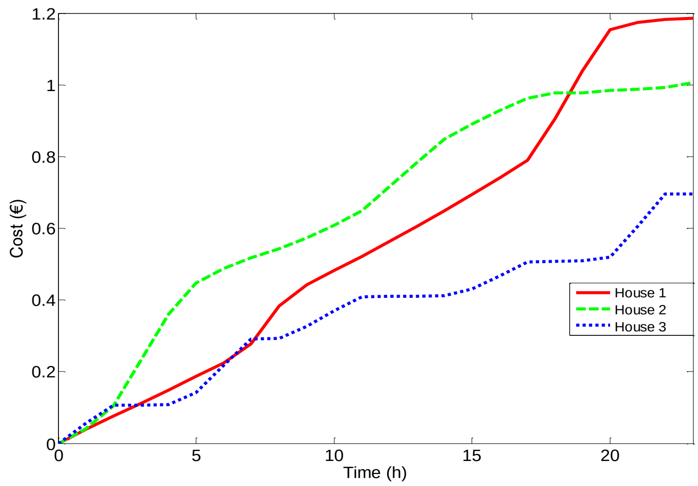

Figure 6.31. Scenario III - Heating/cooling total cost.

Therefore the energy costs, Figure 6.31, decreased in all agents, namely 8%, 9% and 54% comparatively with Scenario I, and 9%, 45% and 25% when compared with Scenario II, as summarized in Table 6.4.

Table 6.4. Scenario III - Cost comparisons

Scenario	**A_1**	**A_2**	**A_3**
I	1,27	1,09	1,27
II	1,39	1,52	0,92
III	1,18	1,00	0,69

6.2.1.4 Scenario IV - Parameterization for comfort benefits

The fourth scenario is focused in maintaining the indoor comfort, all agents want to respect the established temperature gap regardless the required consumption. To accomplish this goal, the temperature penalty was significantly increased, and the consumption parameters decreased, Table 6.5.

Table 6.5. Scenario IV - Penalty values

Parameter	**A_1**	**A_2**	**A_3**
Ξ	50000	50000	50000
ψ	1	1	3
ϕ	0.2	0.2	0.2
φ	0.1	0.1	0.1

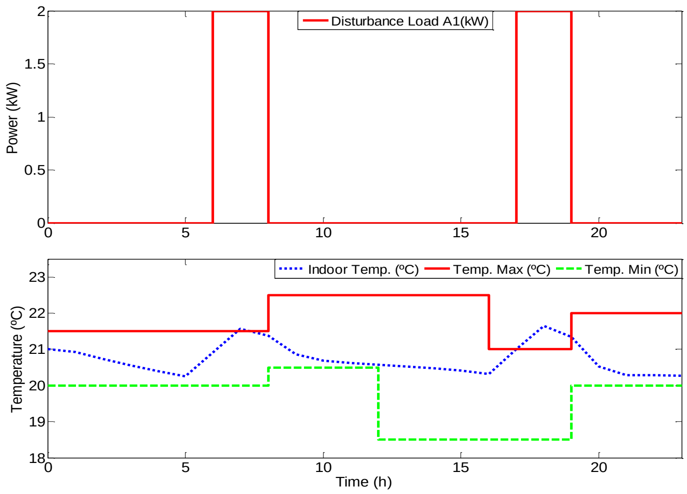

Figure 6.32. Scenario IV - Disturbance forecasting and indoor temperature A_1.

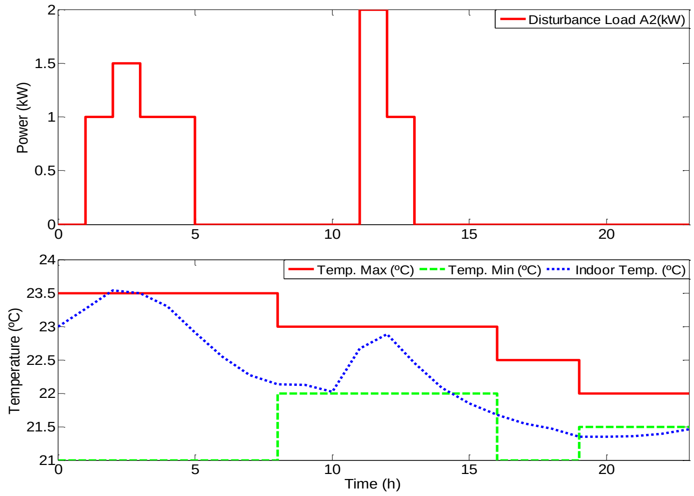

Figure 6.33. Scenario IV - Disturbance forecasting and indoor temperature A_2

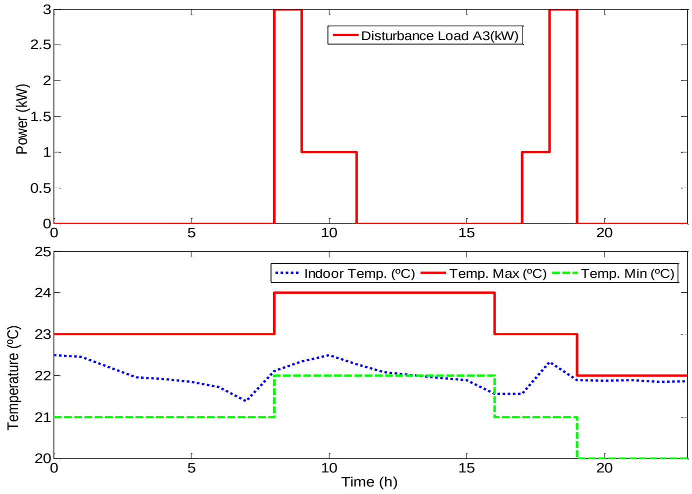

Figure 6.34. Scenario IV - Disturbance forecasting and indoor temperature A_3

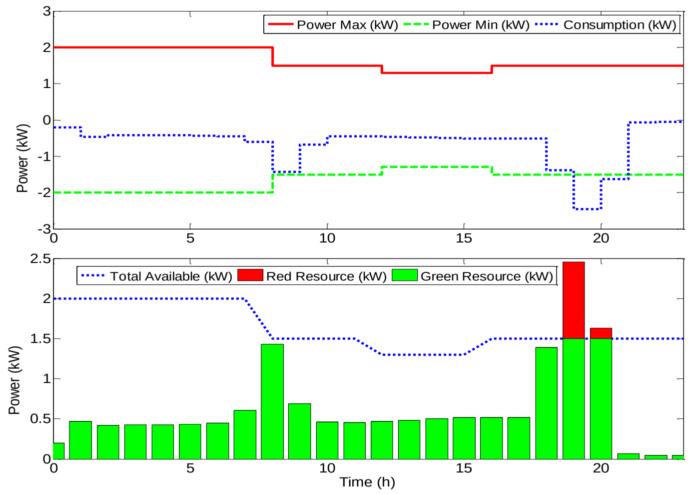

Figure 6.35. Scenario IV – A_1 power profile.

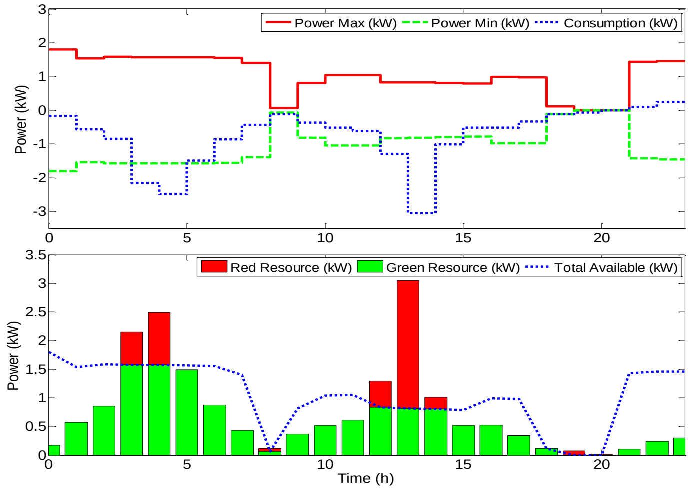

Figure 6.36. Scenario IV - A_2 power profile.

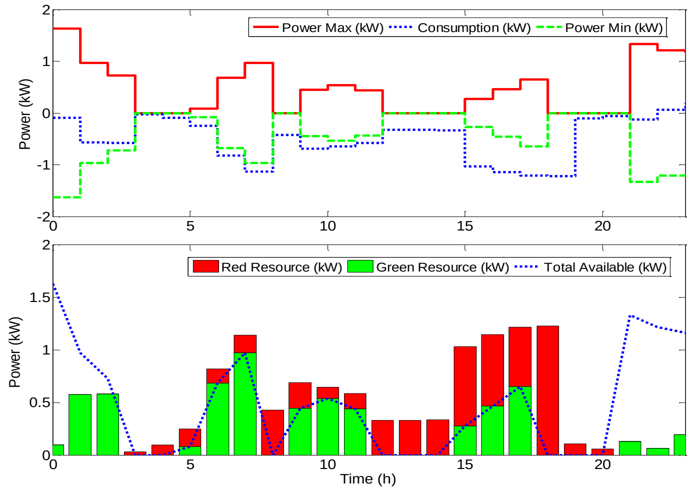

Figure 6.37. Scenario IV - A_3 power profile.

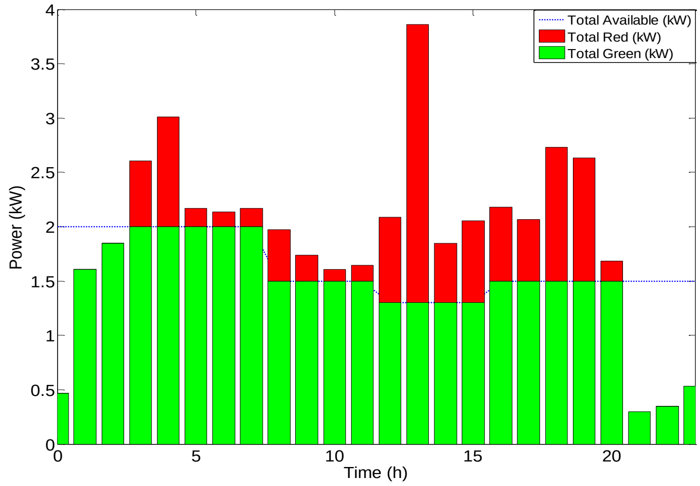

Figure 6.38. Scenario IV - Global consumption characterization.

As can be seen in Figure 6.32, Figure 6.33 and Figure 6.34 in all the indoor temperatures are mostly maintained inside the comfort gap.

As consequence, the power constraints, Figure 6.35, Figure 6.36 and Figure 6.37, are violated and the *red* resource consumption increased significantly,

Figure 6.38.

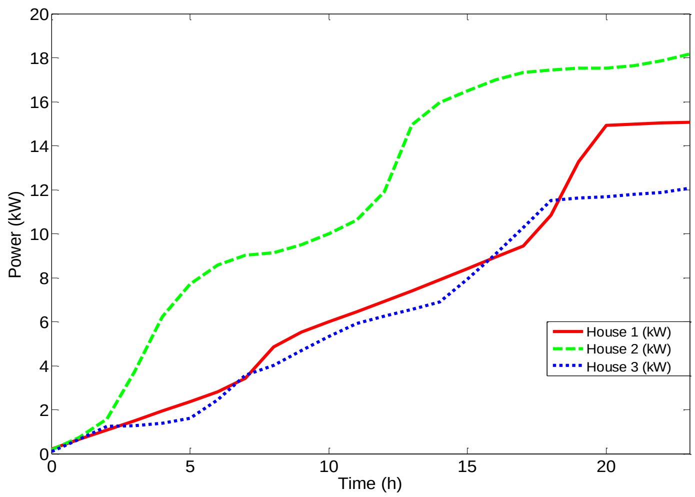

Figure 6.39. Scenario IV - Power profile.

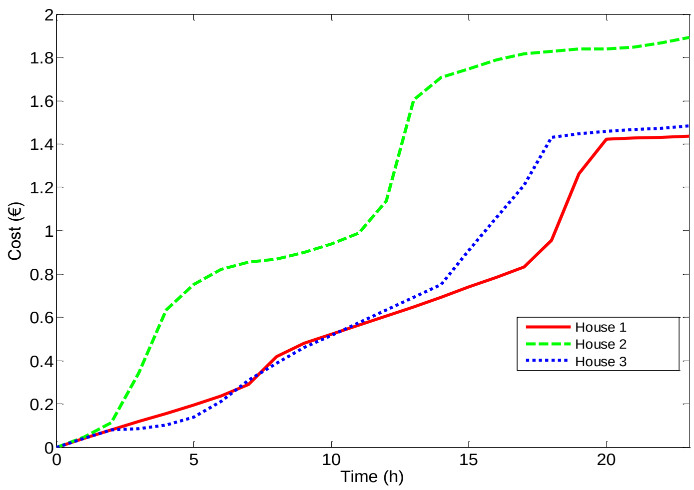

Figure 6.40. Scenario IV - Heating/cooling total cost.

Being now the comfort a priority it’s quite clear that the controller tries to accomplished the pre-defined comfort range leading to a consumption and cost surplus.

As expected, distinct results were obtained in the several proposed scenarios. Figure 6.41 summarize the obtained costs results for the 24hours simulation.

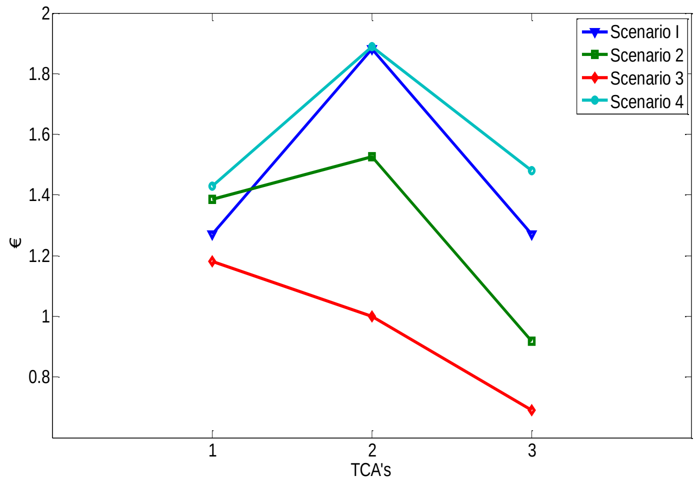

Figure 6.41. Daily heating/cooling total cost.

Comparing the economic differences between scenarios, the third scenario has shown to be the most economical; the parameters penalizing the consumption were significantly increased, leading to a situation of less energy usage. However, this decreased consumption led to a higher indoor temperature deviation from the established boundaries. On the other hand, Scenario IV was the most expensive. In this scenario the penalty value in the temperature constraint was increased, showing that the consumers were only concerned in maintaining the temperature inside the boundaries. Thus, all the necessary resources were consumed, leading to higher costs, in order to respect the comfort limits. The possibility of obtaining comfort in detriment of the cost may be important in various situations. For example: To acclimatize rooms with children or areas in laboratories and/or hospitals. Remark that, despite this comfort preference, the cost function (in due proportion given by the parameters) also minimizes all the other terms.

The parameterizations from the first and second scenarios have shown to be the most balanced, with a compromise between comfort and costs.

6.3 Access order with variable hourly sequence

In this chapter it is considered that the sequence access order may vary hourly (Barata et al., 2013a). The TCA bids are made according to the consumption needs. Each TCA is isolated (no thermal interactions are considered), has a known fixed 24 hours consumption profile and it is established a priority level from 1 (low) to 3 (high), that indicates how important that hour is in terms of consumption. Thus, the hours with high priority levels indicates high consumption and consequently a higher bid value, Table 6.7.

6.3.1 Algorithm II - Implemented sequential scheme with variable hourly sequence

As mentioned it is considered that the sequence order was already stablished by a previous auction, but in this chapter, the access sequence order vary hourly. The hourly access sequence is storage in $A_O(N_S \times H_P)$ as exemplified in Table 6.6 for N_S=5 and H_P=24. Each agent predicts the consumption and subtracted it to maximum available communicates that information to the next on the sequence list. Remark that, only the divisions that thermally interact pass to each other the information about future indoor temperatures.

Table 6.6. Example of hourly access order sequence to *green* energy

	Time (h)						
	1	**2**	**3**	**4**	**…**	**23**	**24**
Access order	TCA 1	TCA 3	TCA 5	TCA 1	…	TCA 4	TCA 1
	TCA 2	TCA 1	TCA 1	TCA 2	…	TCA 5	TCA 2
	TCA 5	TCA 2	TCA 3	TCA 5	…	TCA 3	TCA 3
	TCA 4	TCA 4	TCA 2	TCA 4	…	TCA 2	TCA 4
	TCA 3	TCA 5	TCA 4	TCA 3	…	TCA 1	TCA 5

Algorithm II - DSM-DMPC Implemented sequential scheme with variable hourly sequence

Required for all TCA's: Thermal disturbances, comfort temperature gap, hourly constraints parameters and hourly auction bid.

For all TCA's W_i initialize:

Cw_l^i fixed consumption within H_P $(1 \times H_P)$

$\boldsymbol{B_V}$ bid value by hour inside the H_P $(1 \times H_P)$

$\boldsymbol{A_O}$ access order to *green* resource is established within the H_P $(N_S \times H_P)$.

for k=1 **to** N_C

for i=1 **to** N_S(the number of TCA's)

Get the access order at current instant, A_O(k)

Apply to all TCA $u_l^i(k-1: k-1+H_P)$from k-1 instant to obtain $T_l^i(k: k+H_P)$

Communicate temperature predictions to adjacent TCA's

Update available *green* resource

$$\overline{U}_i(k: k+H_P) = \overline{U}_i(k: k+H_P) - \sum_{l=1}^{Nd_i} Cw_l^i(k: k+H_P)$$

Calculate the optimal control sequence $u_l^i(1: H_P)$ solving OP_i (5.1)-(5.11) with power constraints given by $\underline{U_i}$ and $\overline{U}_i$

Update available green resource values for next TCA

$$\overline{U}_{i+1}(k: k+H_P) = \overline{U}_i(k: k+H_P) - \sum_{l=1}^{Nd_i} u_l^i(k: k+H_P)$$

end for

Update batteries available energy

end for

Remark: generically, $X(k: k+H_P)$ represents a line vector $(1 \times H_P)$ containing values from $x(k)$ to $x(k+H_P)$, and $Y(p, k: k+H_P)$, represents the line p of a matrix $(P \times H_P)$ containing values from y(p, k) to y$(p, k+H_P)$.

6.3.2 Results

Figure 6.42 presents the outdoor temperature and Figure 6.43 to Figure 6.45, presents the known fixed 24 hours consumption profile and priority level from the three TCA's.

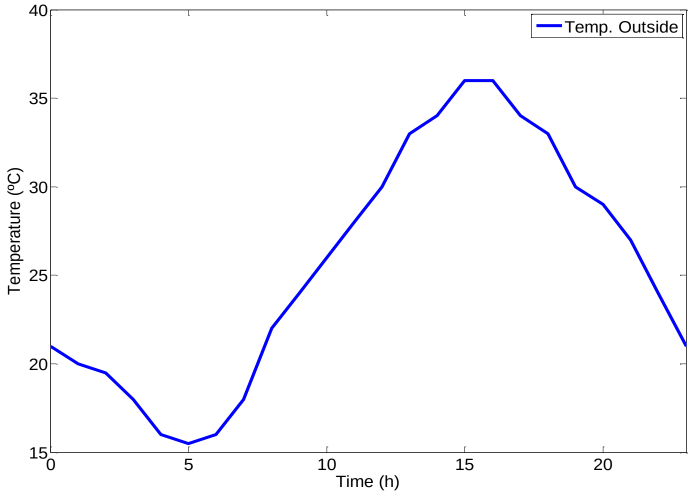

Figure 6.42. Outdoor temperature forecasting (T_{oa}).

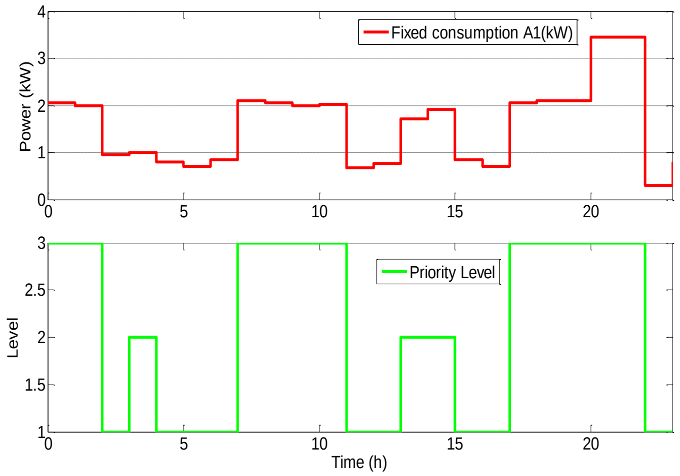

Figure 6.43. Fixed consumption profile Cw_1^1, and priority level of TCA1.

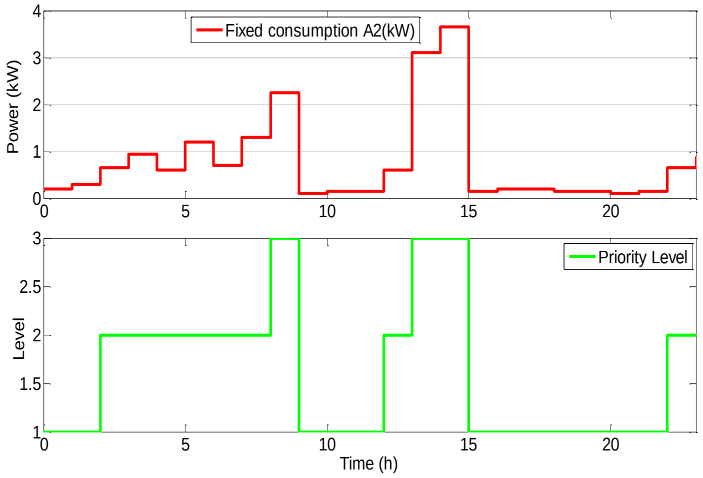

Figure 6.44. Fixed consumption profile Cw_1^2, and priority level of TCA2.

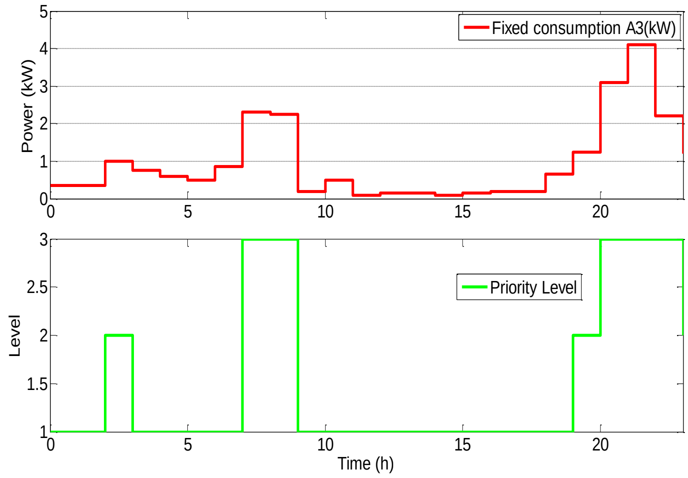

Figure 6.45. Fixed consumption profile Cw_1^3, and priority level of TCA3.

As mentioned, the priority level presented is stablished according the consumption needs. Thus, higher consumption represents higher priority levels, and consequently higher bid values, as presented in Table 6.7.

Table 6.7. Bid value for each consumption level by agent.

Consumption	Priority Level	House 1	House 2	House 3
0-1 kW	1	2/5×0.09	3/5×0.09	1/2×0.09
1-2 kW	2	7/10×0.09	4/5×0.09	2/3×0.09
>2 kW	3	8.5/10×0.09	9/10×0.09	3/4×0.09

The bid value establishes an order to access to the resource, being the *green* resource consumption made by the agents sequentially by that order. The first agent consumes and the remainder *green* resource is passed to the next agent as the maximum green available resource. As mentioned, when the *green* resource becomes insufficient to satisfy all the demand, the *red* is available. The *red* resource consumption implies a penalty in the final cost function (5.1) due to the soft constraint violation imposed by the maximum available *green* resource is exceeded.

A scheme of the system implemented is shown in the next picture.

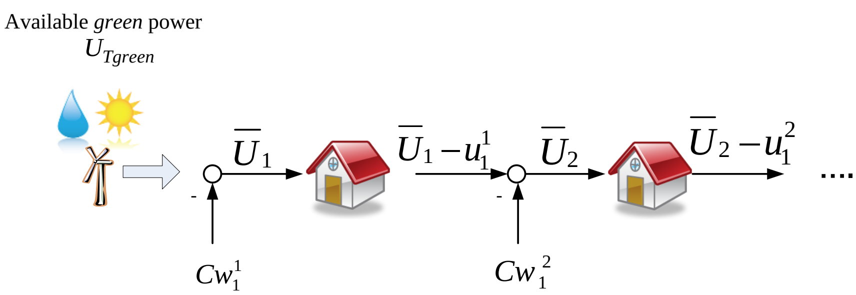

Figure 6.46. Implemented system.

$$Cw_l^i = \left[cw_l^i(k), \dots, cw_l^i(k + H_P)\right]^T \tag{6.1}$$

$$U_{Tgreen} = \left[\left|u_{Tgreen}(k)\right|, \dots, \left|u_{Tgreen}(k + H_P)\right|\right]^T \tag{6.2}$$

$$u_l^i = \left[\left|u_l^i(k)\right|, \dots, \left|u_l^i(k + H_P)\right|\right]^T \tag{6.3}$$

where, for a generic TCA i at the control horizon, $\overline{U}_i$ represents the *green* available resource for indoor comfort , U_{Tgreen} represents the *green* available total resource, Cw_l^i the fixed consumption profile from TCA i division l and u_l^i the used power to heating/cooling the division l inside TCA i, that results from the optimization program.

It is considered that all houses have the same outdoor temperature presented in Figure 6.42. The thermal characteristics, load disturbances profile and comfort temperature bounds are different for all houses. Agents can also have distinct penalties on power and temperature constraints violations, they can hourly privilege comfort or cost according to consumer choice. Here, is assumed that the penalty values of each agent are always the same. Table 6.8, shows the used parameters.

Table 6.8**.** Scenario parameters.

Parameter	**A$_1$**	**A$_2$**	**A$_3$**	**Units**
R_{eq}	50	25	75	ºC/kW
C_{eq}	9.2×10^3	4.6×10^3	11×10^3	kJ/ºC
Ξ	100	100	300	-
ψ	500	200	300	-
ϕ	2	2	2	-
φ	1	1	1	-
Δt	1	1	1	h
H_P	24	24	24	-
$T(0)$	24	23	24	ºC

As a result from the hourly variation of the priority levels, the bid values also vary hourly yielding distinguish access orders as showed in Figure 6.47.

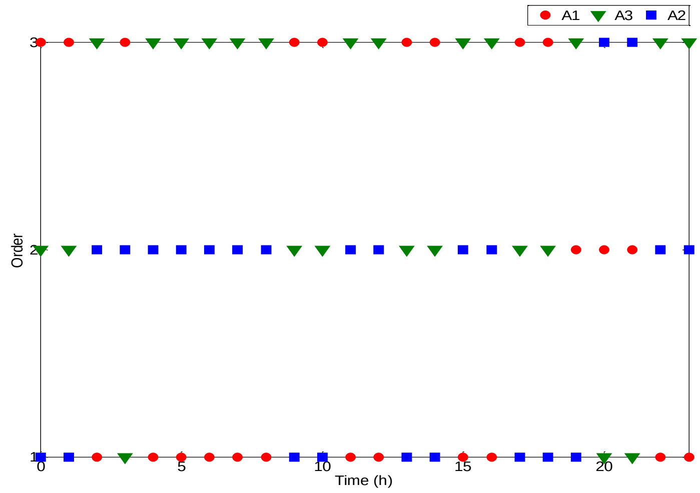

Figure 6.47. Access order.

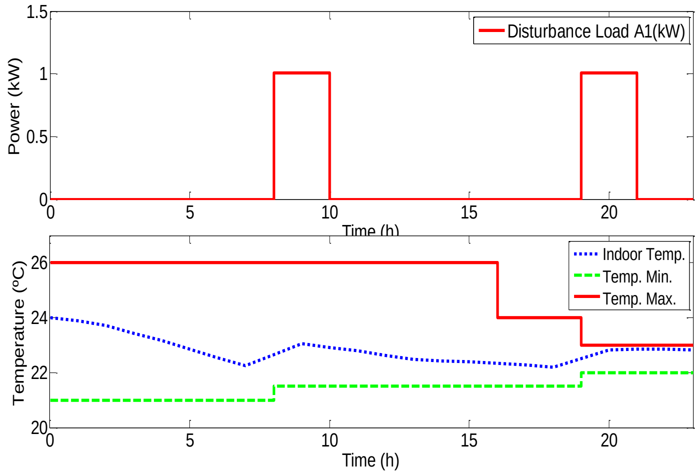

Figure 6.48. Disturbance forecasting and indoor temperature A_1.

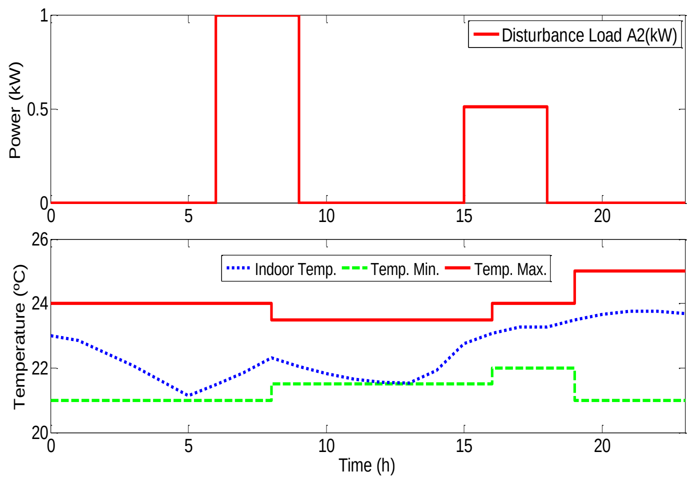

Figure 6.49. Disturbance forecasting and indoor temperature A_2.

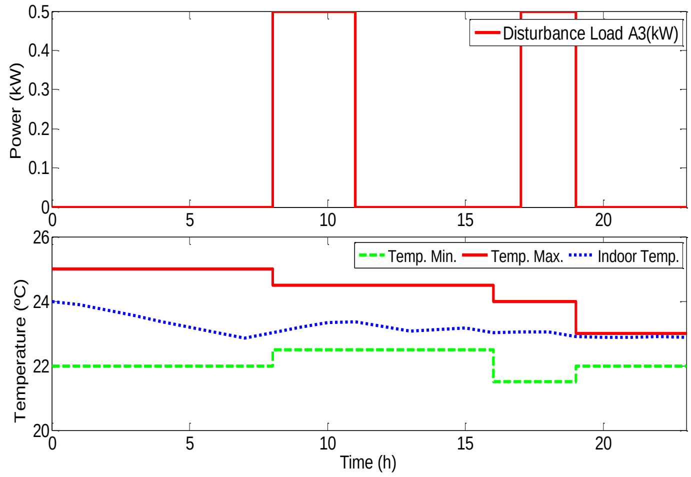

Figure 6.50. Disturbance forecasting and indoor temperature A_3.

The thermal disturbances forecasts and the indoor temperature with its constraints for the TCA, A_1, A_2 and A_3 have the profile presented in, Figure 6.48, Figure 6.49 and Figure 6.50 respectively, and despite it and the access order variability, it can be seen in that the indoor temperatures are always inside their narrow bounds. Taking advantage of the predictive knowledge of the disturbance and making use of the space thermal storage, it can also be seen that the MPC treats the indoor temperature before the disturbance beginning.

The Figure 6.51, Figure 6.52 and Figure 6.53 show for TCA, A_1, A_2 and A_3 respectively, the used power to acclimatize the spaces and the available *green* resource to do it. Remark that to the *green* resource value must be subtracted the fixed consumption and then, the remainder represents the maximum available power to provide comfort. Thus, in these figures the "*Power Max*" represents the power constraint, $\overline{U}_i = \overline{U}_{i-1} - u_{i-1}^l - Cw_l^i$, "*Green resource*" $\overline{U}_{i-1} - u_{i-1}^l$, and "*Consumption*" represents u_i^l.

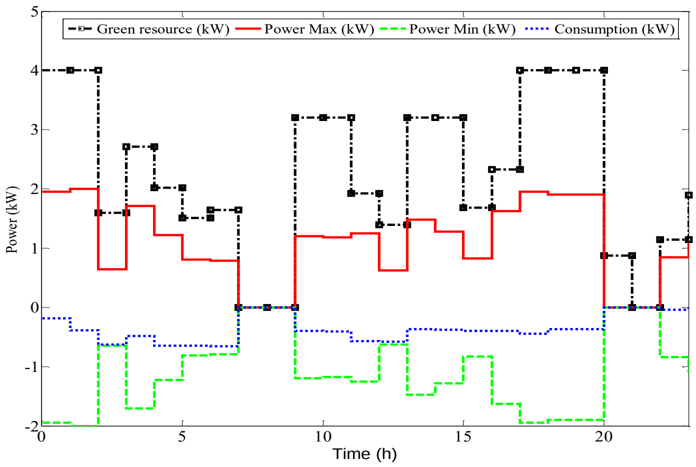

Figure 6.51. Consumption and constraints to heat/cool A_1.

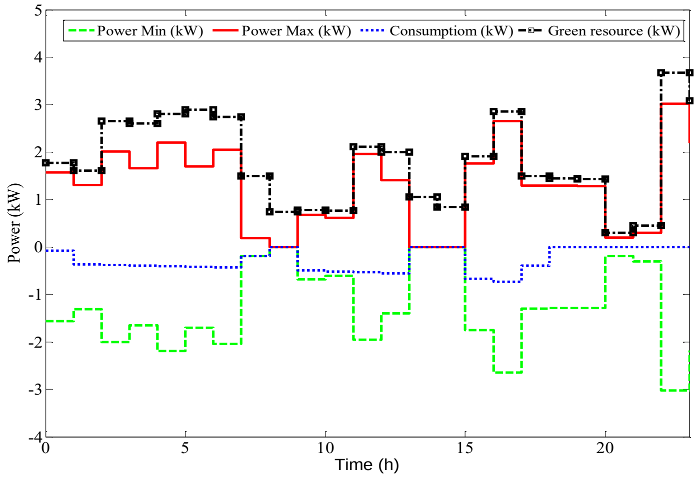

Figure 6.52. Consumption and constraints to heat/cool A_2.

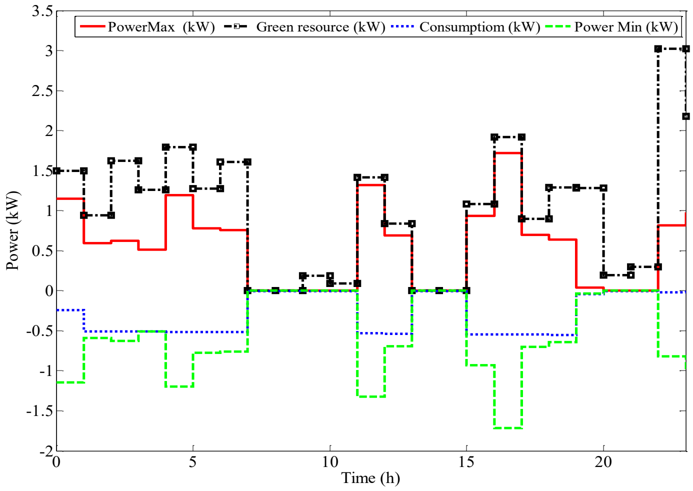

Figure 6.53. Consumption and constraints to heat/cool A_3.

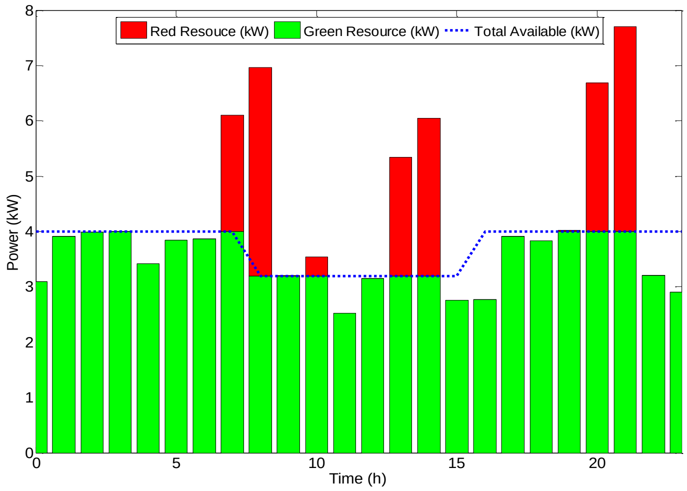

Figure 6.54. Global consumption.

In Figure 6.51 to Figure 6.53, it can be seen that the comfort constraints are respected, the used power to heat/cool the space is maintained inside the constrained bounds. Note that when the resource is null the consumption is also null. Figure 6.54 shows the global used power and characterized it in terms of type of consumed power.

$$U_{used}(k) = \sum\left[\left|u_l^i(k)\right| + Cw_l^i\right].$$

It can be seen in Figure 6.54, that in the most demanding periods, the maximum *green* available resource is exceeded and the *red* resource must be consumed.

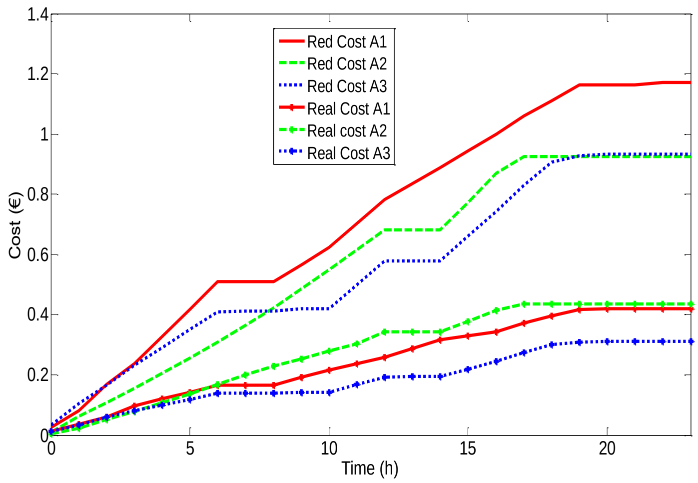

Figure 6.55. Heating/cooling total cost.

Figure 6.55 illustrates the effectiveness of the approach and demonstrates the advantage of the auction. For each one of the agents it can be seen that the "*Real Cost*" is much lower than the cost of not to bid in auction and only consume the *red* resource "*Red Cost*".

6.4 Conclusions

In this chapter, a distributed MPC control technique was presented in order to provide thermal house comfort. The solution obtained solves the problem of controlling multiple subsystems dynamically coupled and also exposed to a coupled constraint. Each subsystem solves its own problem by involving its own state predictions or from neighbourhoods and the shared constraints. It could be observed through the simulations and result's analysis that suitable dynamic performances were obtained. The built system is flexible in two ways. It allows in each auction the agents to bid higher or lower in accordance with their needs and, by changing the penalty values during the day, consumers can shift hourly between indoor comfort and lower costs. Knowing in advance the disturbance forecasts allows agents to make their bid and achieve significant savings at the end of the day.

The distributed MPC control technique, along with a thermal-electrical modular scheme, was validated in order to provide thermal house comfort, with strong presence of intermittent/limited

RES environments. The approach spots a control problem of multiple subsystems dynamically coupled and exposed to coupled constraint. Each subsystem solves its own problem by involving its own state predictions and the state predictions of adjacent rooms, available with communication interchange and shared constraints. The changing in penalty values allows consumer to pick between indoor comfort and lower costs.

Chapter 7

DMPC for Thermal House Comfort with Sliding Load

7.1 Introduction

The desired approach here presented intends to take advantage from the innovative technology characteristics provided by future SGs (Korolija et al., 2011). In the smart world, simple household appliances, like dishwashers, clothes dryers, heaters or air conditioners are assumed to be fully controllable in order to achieve the network maximum efficiency. Renewable energies will be a common presence and any kWh provided by these technologies should not be wasted. Active Demand-Side Management will control the loads in order to adapt them to the available renewable energy source. As mentioned in Chapter 2.2, DSM studies are focused in the development of load control manipulation models (EIA, 2014; Favre-Perrod et al., 2009) and electricity incentive prices to promote load management (Kosek et al., 2013; Chen, 2010). In buildings, DSM is based on an effective reduction of the energy needs by changing the shape and amplitude consumer's load diagrams. So, DSM can involve a combination of several strategies; pricing, load management curves and energy conservation are implemented for a more energy efficient use.

Load shifting is considered a common practice in the management of electricity supply and demand, where the peak energy use is shifted to less busy periods. Properly done, load shifting helps meeting the goals of improving energy efficiency and reducing emissions, smoothing the daily peaks and valleys of energy use and optimising existing generation assets. With new technological advances, DR programmes may shift loads by controlling the function of air conditioners, refrigerators, water heaters, heat pumps and other similar electric loads at maximum demand times. The work here presented is distinct because provides an integrative solution which is able to, in a distributed network with multiple TCAs, adjust the demand to an intermittent limited energy source, using load shift and maintaining the indoor comfort, (Barata et al., 2013c) and more detailed in (Barata et al., 2014c). Figure 7.1, exemplifies a shifting load communication infrastructure.

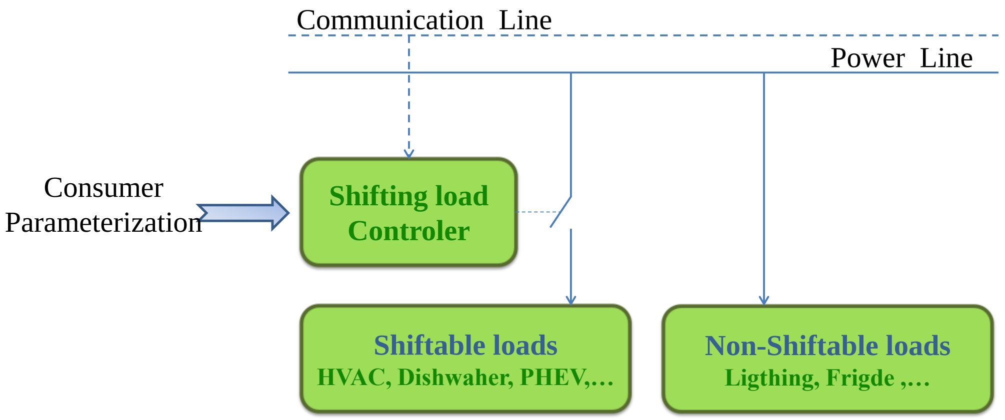

Figure 7.1. Shifting load communication infrastructure.

Thus, due the specificities made in this chapter, the following assumptions are added to the ones made in Chapter 6.1:

- Each division selects the load value (L_V), the duration (L_{Vd}), the turned on time (T_{oT}) and the "sliding level" (S_L) of the "shifted loads". The S_L indicates that the load can be turned on S_L hours before and after the chosen T_{oT};

The next picture illustrates the shifting load characteristics.

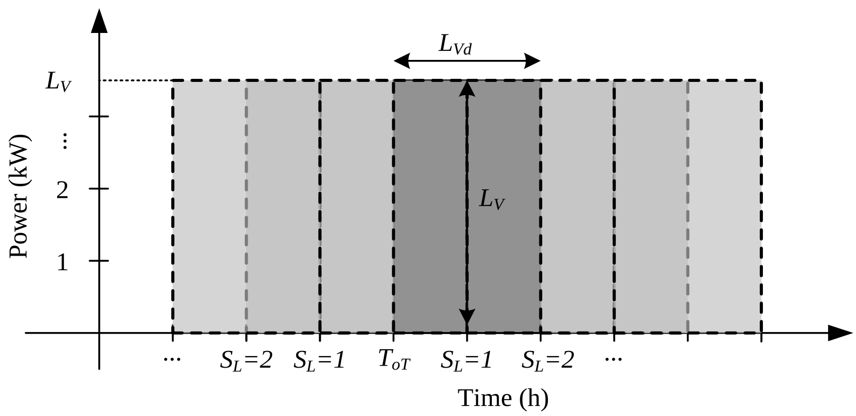

Figure 7.2. Implemented shifting load scheme.

Therefore, using the demand side management, by negotiating the energy price and the consumer comfort, the distributed loads can be managed and shifted in order to guarantee the satisfaction of all constraints. The global system includes an auction (provided by the MO) that, in accordance with the bid value made by the houses/agents, defines an order to access the *green* resource. The *green* resource consumption is made by the agents sequentially by the auction order and the information about the remaining *green* resource is passed to the next agent as the maximum *green* available resource. As mentioned, when *green* resource becomes insufficient to satisfy all the demand, the *red* is available.

7.2 Algorithm III – Implemented shifting and loads allocation scheme

Each one of the systems starts by choosing their loads characteristics, L_V, L_{Vd}, T_{oT} and S_L. With this data, all the possible loads schedule combinations ($PLSC_S$) are establish (see Figure 7.7 *e.g.*). At each time step, it's verified if inside the predictive horizon, any $PLSC_S$ exceeds the maximum available *green* energy $\overline{U}\max_i$. The sequences that are at any instant above the $\overline{U}\max_i$ limit are removed, and the remaining are the feasible load schedule combinations ($FLSC_S$). The $FLSC_S$ are subtracted to $\overline{U}L_i$, and the resulting in a set of combinations $\overline{U}_i$ that are tested in the minimization problem as maximum available *green* resource for comfort (5.1). The hypothesis that provided less consumption is chosen. Once one sequence is started, all the others that are different until the current step time are eliminated until the final load sequence is chosen, *FLSeq*. The total consumption by division and house at any instant can be written as (7.1) and (7.2) respectively, and is pictured in Figure 7.4.

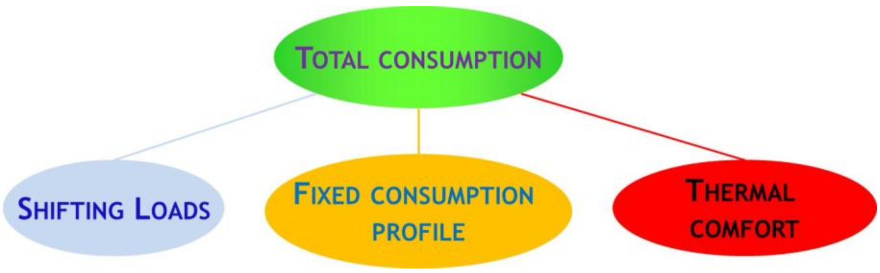

Figure 7.3. Total consumption characterization.

Remark that the total available for comfort for each house (7.3) is used as constraint in the optimization problem. The equations assume the following form,

$$P_l^i(k) = \left|u_l^i(k)\right| + Cw_l^i(k) + FLSeq_l^i(k), \tag{7.1}$$

$$P_i(k) = \sum_{l=1}^{Nd_i} P_l^i(k)\,, \tag{7.2}$$

$$\overline{U}_i(k) = u_{Tgreen}(k) - \sum_{l=1}^{Nd_i} \left(Cw_l^i(k) - FLSeq_l^i(k) \right) - \sum_{\substack{j=1 \\ i \neq j}}^{N_S} P_j(k). \tag{7.3}$$

A simplified scheme of the implemented optimization problem is shown in the next picture, Figure 7.4, followed by the implemented DSM-DMPC algorithm.

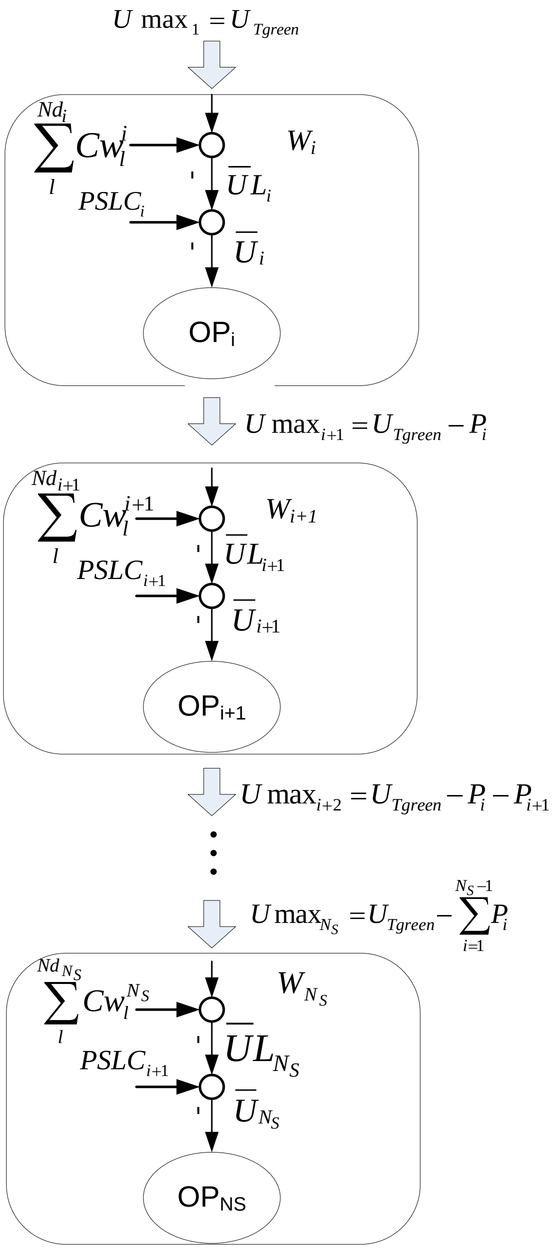

Figure 7.4. Implemented power distribution scheme starting in the Optimization Problem 1 (OP_i) to OP_{NS}.

Algorithm III - DSM-DMPC pseudocode prototype algorithm

For all houses W_i initialize:

$\boldsymbol{L_V}$	load value
$\boldsymbol{L_{Vd}}$	the duration
$\boldsymbol{T_{oT}}$	the turned on time
$\boldsymbol{S_L}$	sliding level
$PSLC_i$	possible schedule loads combinations $(n_{PC} \times H_P)$ with $\boldsymbol{n_{PC}}$ the number of possible combinations
Cw_l^i	fixed consumption within H_P $(1 \times H_P)$
$\boldsymbol{B_V}$	bid value by hour inside the H_P $(1 \times H_P)$
$\boldsymbol{A_O}$	access order to *green* resource is established within the H_P $(N_S \times H_P)$.

for k=1 **to** N_C

for i=1 **to** N_S(the number of TCA's)

Get the access order at current instant, A_O(k)

Apply to all TCA $u_l^i(k-1{:}\,k-1+H_P)$from k-1 instant to obtain $T_l^i(k{:}\,k+H_P)$

Communicate temperature predictions to adjacent TCA's

Update available *green* resource

$$\bar{U}L_i(k{:}\,k+H_P) \leftarrow \bar{U}max_i(k{:}\,k+H_P) - \sum_{l=1}^{Nd_i} Cw_l^i(k{:}\,k+H_P)$$

Built table with all $FSLC_S$

$$FLSC_i(n_{FC}, k{:}\,k+H_P) \leftarrow PLSC_i(n_{FC}, k{:}\,k+H_P) - \bar{U}L_i(k{:}\,k+H_P) \geq 0$$

for t=1 to n_{FC} (number of feasible combinations)

Calculate the optimal control sequence $u_i(1{:}H_P)$ solving OP_i (5.1)-(5.11) with power constraint given by $\bar{U}_i(k{:}\,k+H_P) \leftarrow FLSC_i(t, k{:}\,k+H_P)$

$U_{pred_i}(t) \leftarrow \sum u_i(1{:}\,H_P)$

if $U_{pred_i}(t) < U_{pred_i}(t-1)$ **then**

$FLSeq_i(1{:}\,k) \leftarrow FSLC_i(t, k{:}\,k+H_P)$

end if

end for

Eliminate from $PLSC_i$ all the sequences that are different from $FLSeq_i(1{:}\,k)$

Update available *green* resource values for next TCA

$$\bar{U}_{i+1}(k{:}\,k+H_P) = \bar{U}_i(k{:}\,k+H_P) - \sum_{l=1}^{Nd_i} u_l^i(k{:}\,k+H_P)$$

end for

Update batteries available energy

end for

As mentioned the algorithm is sequential, and for a better understanding of the implemented power distribution scheme, the access order is W_1, W_2 and so on. Therefore, for a certain instant, is considered that W_1 was the one that made the highest bid, W_2 made the second highest, always sequentially until W_{N_S}. In Figure 7.4, the available power for W_1 is given by the predicted *green* total available resource $\overline{U}max_1 = U_{T_{green}}$ at the control horizon (7.5), and them the fixed consumption (7.4) is subtracted resulting in $\overline{U}L_i$. As mentioned, the $PLSC_S$ are compared inside the predictive horizon with $\overline{U}L_i$, and the ones that exceeds at any instant limit are removed, and the remaining are $FLSC_S$. The $FLSC_S$ are subtracted to , and the resulting in a set of combinations $\overline{U}_i$.. These combinations are the power constraint (5.10) and are tested in the OP_i (5.1). The combination that generate lower consumption, u_i , is chosen. Then, the information about the available *green* energy is passed for the next house, $\overline{U}max_i$.

For a generic Agent *i* at the control horizon $U_{T_{green}}$ represent the *green* available total resource, Cw_l^i the fixed consumption profile and $u_l^i$the used power to heating/cooling the space that results from the optimization program. These parameters are express by the vectors (7.4)-(7.6),

$$Cw_l^i = \left[cw_l^i(k), \ldots, cw_l^i(k + H_P)\right]^T, \tag{7.4}$$

$$U_{Tgreen} = \left[\left|u_{Tgreen}(k)\right|, \ldots, \left|u_{Tgreen}(k + H_P)\right|\right]^T, \tag{7.5}$$

$$u_l^i = \left[\left|u_l^i(k)\right|, \ldots, \left|u_l^i(k + H_P)\right|\right]^T. \tag{7.6}$$

In the built algorithm it is considered that the access order to the green resource is established hourly according to bid value made in auction by each agent, and therefore, at each instant the defined access sequence must be applied. Another feature provided by the implemented system is that each house can have different hourly penalties, allowing the consumer to choose between more/less comfort and cost during the day.

7.3 Results

The presented results were obtained with an optimization MATLAB® routine that finds a constrained minimum of a quadratic cost function that penalizes the sum of the several objectives (5.1).

7.3.1 **One house scenario**

To simplify better understand the used approach, the first results here present show only the shifting loads procedure for one house represented by one division with thermal disturbance (Q_{Pd}), Figure 7.6 (no fixed consumption profile and storage are considered). Table 7.1 shows the used scenario parameters. The outdoor temperature forecast, Figure 7.5, considers 90% accuracy to within +/- 2°C on the next day.

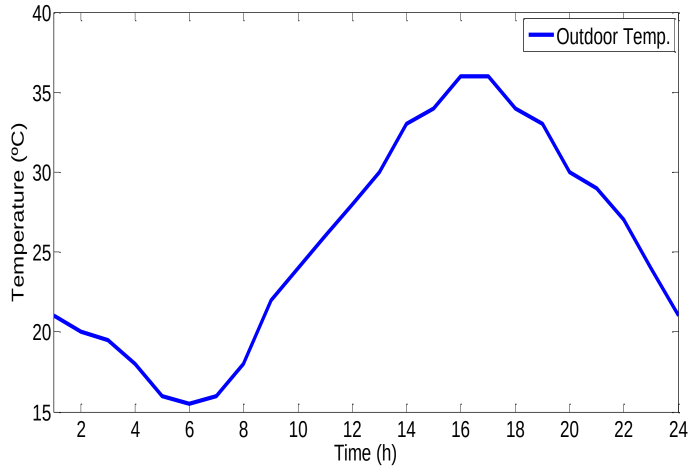

Figure 7.5.Outdoor temperature forecasting (T_{oa}).

Table 7.1.Scenario parameters

R_{eq}(°C/kW)	C_{eq}(kJ/°C)	Ξ	Ψ	ϕ	φ	Δt(h)	H_P	N_C	$T(0)$ (°C)
50	9.2×10^3	500	500	2	1	1	24	24	21

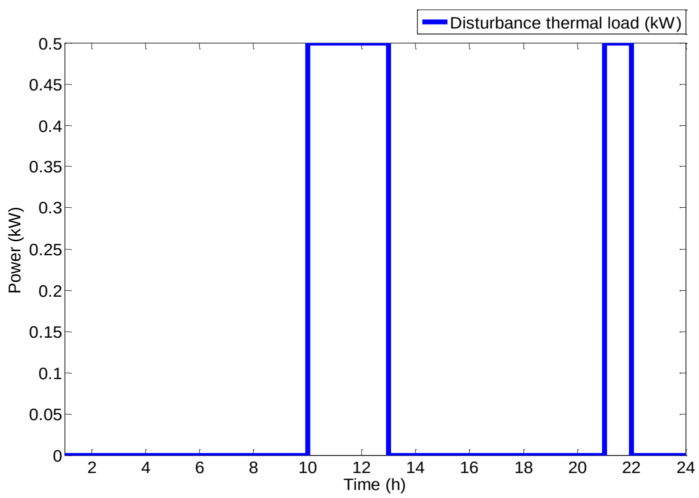

Figure 7.6. Thermal disturbance forecasting.

The *Loads* that can be daily shifted have the characteristics present in the next Table 7.2, and Figure 7.7 shows all the possible 56 loads combinations in the 24hours period.

Table 7.2. Shifted loads characteristics

Loads	L_V (kW)	L_{Vd} (h)	T_{oT} (h)	S_L (h)
Load 1	3	2	8	3
Load 2	2	3	18	4

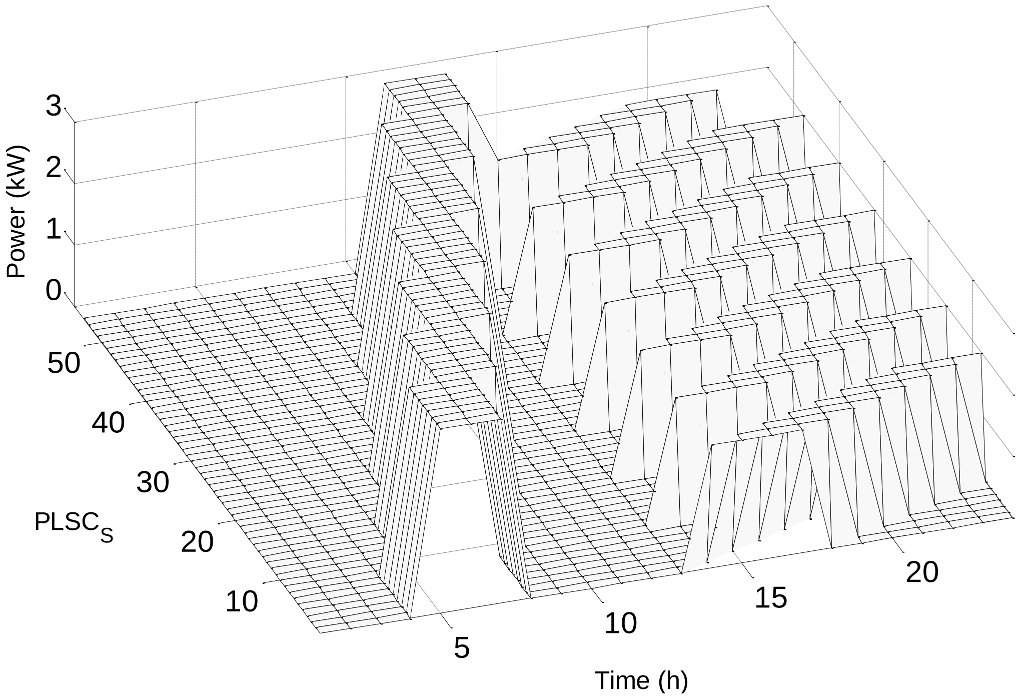

Figure 7.7. Possible loads schedule combinations ($PLSC_s$).

The system tests all combinations present in Figure 7.7, and as mentioned above, the hypotheses that do not respect the maximum predicted *green* resource are initially discharge, and the remaining ones the $FLSC_S$, Table 7.3, are tested in (5.1).

The sequence *FLSeq*, where mostly *green* energy is consumed, the costs are lower and the indoor comfort range is respected is found.

Table 7.3. Feasible Loads Sequence Combinations

FLSC	**Time (h)**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	0	0	0	0	0	0	0	0	3	3	3	0
2	0	0	0	0	0	0	0	0	3	3	3	0
3	0	0	0	0	0	0	0	0	3	3	3	0
4	0	0	0	0	0	0	0	0	3	3	3	0
FLSC	**Time (h)**											
	13	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
1	0	2	2	2	2	0	0	0	0	0	0	0
2	0	0	2	2	2	2	0	0	0	0	0	0
3	0	0	0	2	2	2	2	0	0	0	0	0
4	0	0	0	0	2	2	2	2	0	0	0	0

In Figure 7.8 are the total energy costs of the *FLSC*$_S$ shown in Table 7.3, and can be seen that the chosen sequence is the less expensive.

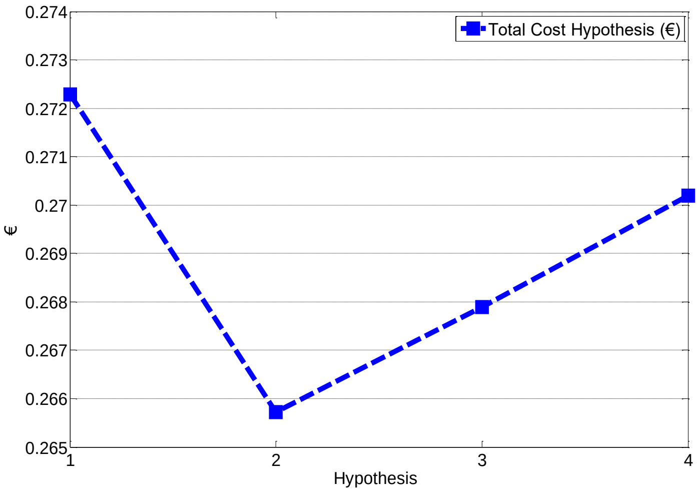

Figure 7.8. Total energy costs of *FLSC*$_S$.

Figure 7.9, show the chosen load sequence, *FLSeq*, and the available *green* energy to allocate the loads.

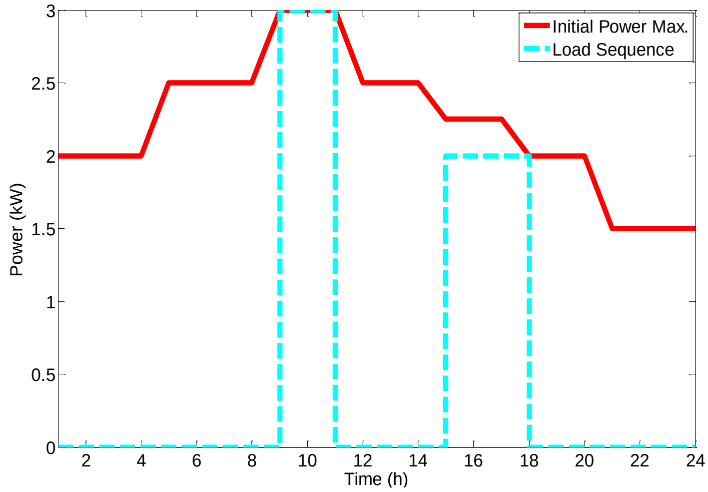

Figure 7.9. Maximum available *green* energy and chosen sequence.

In order to minimize the energy costs by consuming only *green* resource, the implemented algorithm chooses the gaps that fit properly in the maximum available *green* energy.

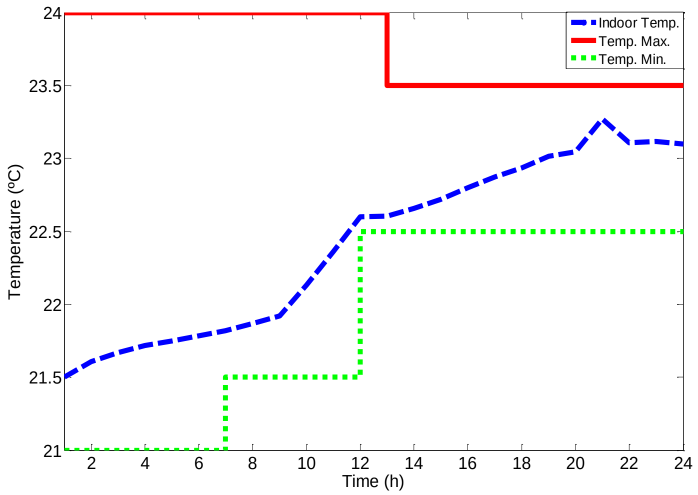

Figure 7.10. Indoor temperature.

The comfort limits varies during the 24h period, and Figure 7.10 shows that the indoor temperature is always maintained inside the comfort limits being the optimization problem able to respect the temperature and power constraint Figure 7.11.

The periods between 9-11h and 15-18h are extremely demanding, all *green* energy is consumed by the shifted loads, with no remaining one for comfort proposes.

Although, Figure 7.10 shows that in that periods the algorithm choose to not use the red resource and, taking advantage of the prediction horizon, pre-heat or pre-cool the spaces when only renewable resource is available.

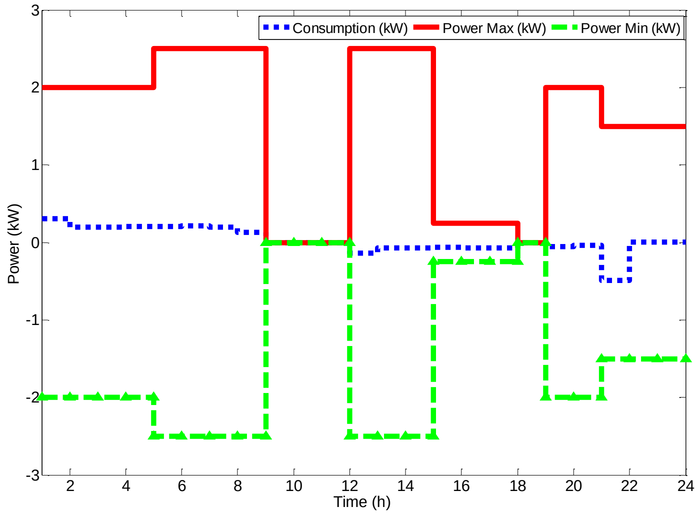

Figure 7.11. Used power to heat/cool the space and the maximum *green* resource available for comfort.

7.3.2 Distributed scenario

It is considered that all houses are represented by one division and have the same outdoor temperature presented in Figure 7.5. The used parameters are presented in Table 7.4.

Table 7.4. Distributed scenario parameters

Parameter	**A_1**	**A_2**	**A_3**	**Units**
R_{eq}	50	25	75	ºC/kW
C_{eq}	9.2×10^3	4.6×10^3	11×10^3	kJ/ºC
Ξ	100	100	300	-
$\boldsymbol{\psi}$	500	200	300	-
$\boldsymbol{\phi}$	2	2	2	-
$\boldsymbol{\varphi}$	1	1	1	-
$\boldsymbol{\Delta t}$	1	1	1	h
$\boldsymbol{H_P}$	24	24	24	-
$\boldsymbol{T(0)}$	21	23	24	ºC

The batteries capacity is 3kWh. To incentive the clean resource consumption, it is considered that the *green* energy price per kWh has a maximum auction value (0.09€/kWh) always cheaper than the *red* energy price (0.17€/kWh). Table 7.5 shows the bid value for each one of the priority levels that, as mentioned, are established according the fixed consumption profile.

Table 7.5. Bid value for each consumption level by TCA

Consumption	Priority Level	TCA 1	TCA 2	TCA 3
0-1 kW	1	2/5×0.09	3/5×0.09	1/2×0.09
1-2 kW	2	7/10×0.09	4/5×0.09	2/3×0.09
>2 kW	3	8.5/10×0.09	9/10×0.09	3/4×0.09

The load disturbances profile, comfort temperature bounds and shifted loads characteristics are different for all houses, Table 7.6.

Table 7.6. Shifted loads characteristics for distributed scenario

TCA	Loads	L_V (kW)	L_{Vd} (h)	T_{oT} (h)	S_L (h)
1	Load 1	1	2	7	1
	Load 2	2	4	18	2
2	Load 1	2	3	9	1
	Load 2	2	2	21	2
3	Load 1	3	3	8	1
	Load 2	3	3	13	1

In all houses, the fixed consumption profile, Cw_1^1, Cw_1^2 and Cw_1^3 and its priority level, are known within a 24h period and are depicted in Figure 7.12, Figure 7.13 and Figure 7.14.

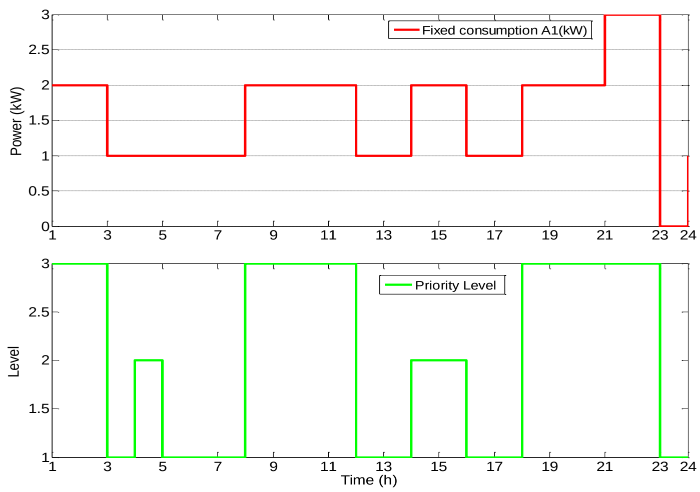

Figure 7.12. Fixed consumption profile Cw_1^1, and priority level of TCA1.

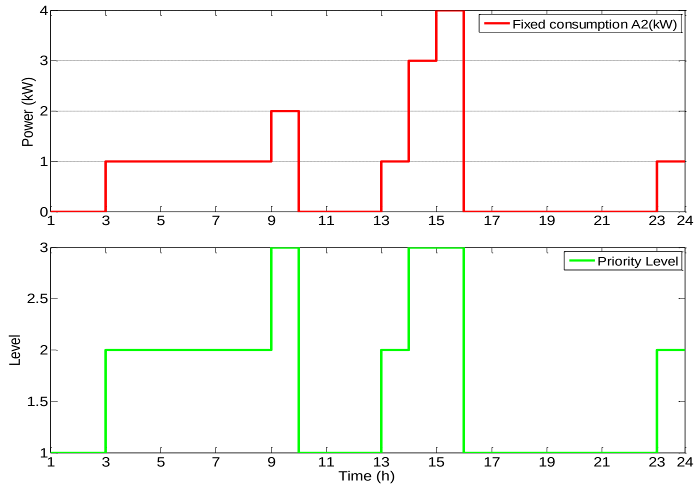

Figure 7.13. Fixed consumption profile Cw_1^2, and priority level of TCA2.

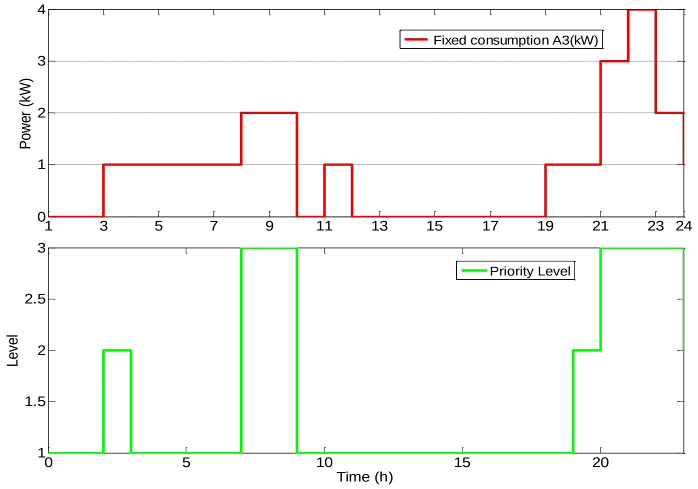

Figure 7.14. Fixed consumption profile Cw_1^3, and priority level of TCA3.

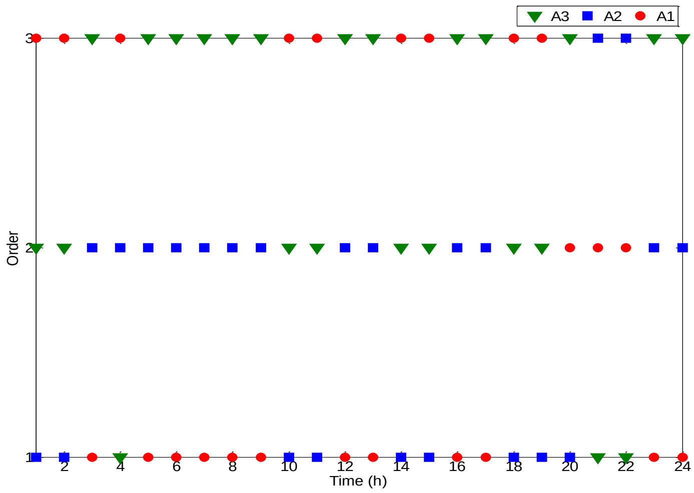

Figure 7.15. Access order.

As a result from the hourly variation of the priority levels, the bid values also vary hourly yielding distinguish access orders as showed in Figure 7.15.

The thermal disturbance profile is known within a 24 hour period, and is related with thermal loads generated by occupants, direct sunlight, electrical devices or doors and windows aperture to recycle the indoor air.

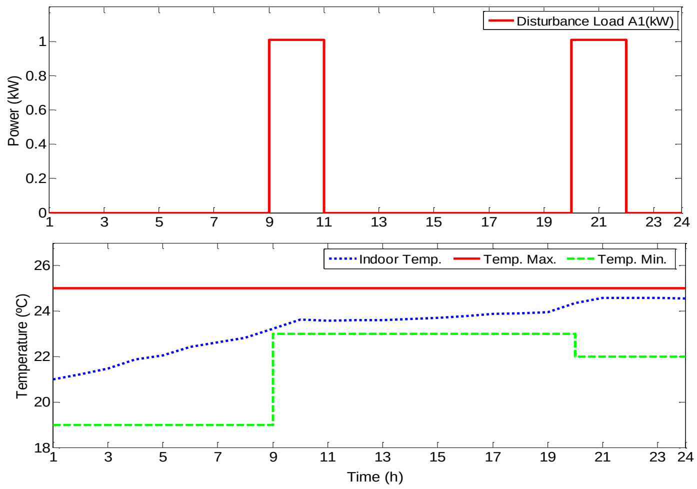

Figure 7.16. Disturbance forecasting and indoor temperature A_1.

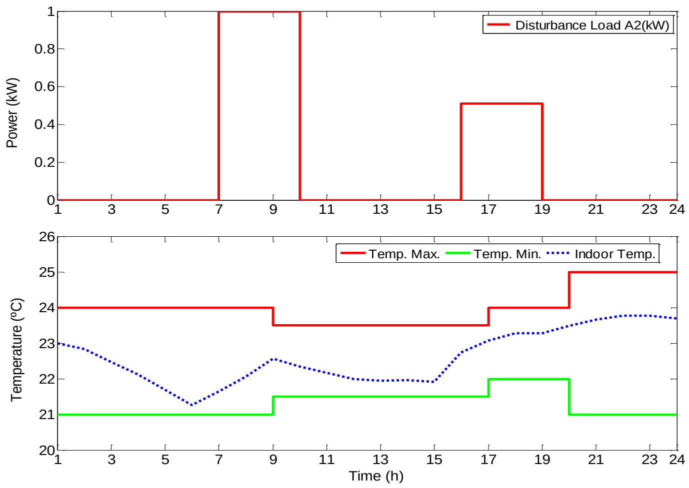

Figure 7.17. Disturbance forecasting and indoor temperature A_2.

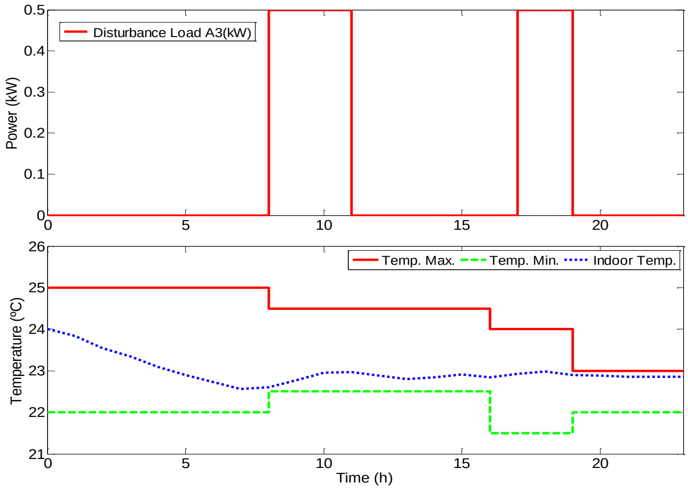

Figure 7.18. Disturbance forecasting and indoor temperature A_3.

In Figure 7.16, Figure 7.17 and Figure 7.18, it can be seen that the comfort constraints are respected, the indoor temperature is always inside the comfort zone in all houses. Taking advantage of the predictive knowledge of the thermal disturbance and making use of the space thermal storage, it can also be seen that in all houses the MPC treats the indoor temperature before the thermal disturbance beginning. In Figure 7.19 it can be seen that the shifted loads were located in zones with mostly *green* energy available. Note that when the used power is above the daily maximum *green* available resource, means that the *red* resource was consumed. The used power to heat/cool the space is maintained inside the constrained bounds and when the *green* energy is null the used power is also null, Figure 7.20, Figure 7.22 and Figure 7.24 for TCA1, TCA2 and TCA3 respectively.

Remark that the fixed consumption, Cw_1^1, Cw_1^2 and Cw_1^3 represent the base in the power profile in Figure 7.19, Figure 7.21 and Figure 7.23.

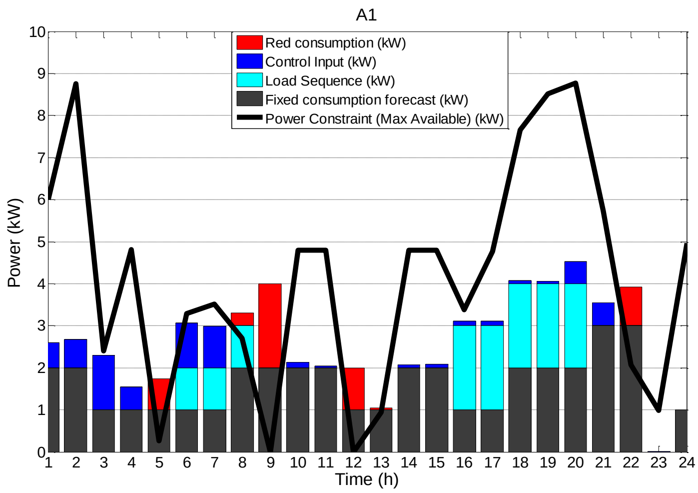

Figure 7.19. Power profile A_1.

Remark that, for example, at time instant t=7, three different types of energy utilization are used. The base, in dark grey, is fulfil with the fixed consumption, above is the shifted load and on top is the used power for comfort. In this instant the total consumption is maintained within the power constraint. On the other hand, at instant t=9, with no available *green* power, all the fixed consumption of 2kW is made with red resource.

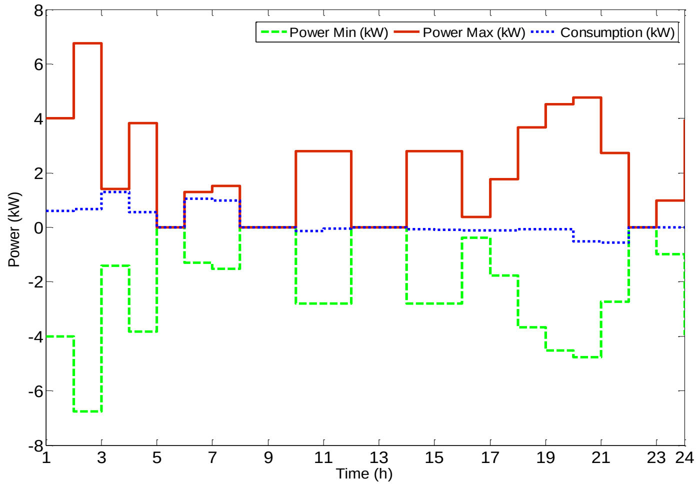

Figure 7.20. Control input profile A_1

In Figure 7.21, it can be seen that the shifted loads of house 2 were located in zones with mostly *green* energy available.

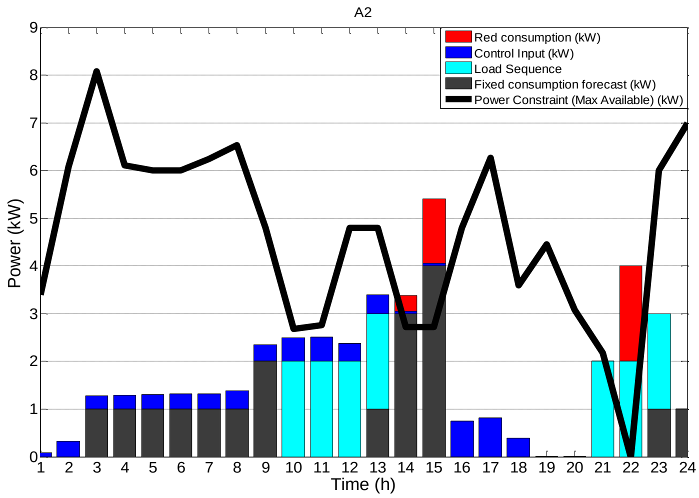

Figure 7.21. Power profile A_2.

The used power to heat/cool the space is always maintained inside the constrained bounds been the clean resource consumed only when is available. Note that when the used power to satisfy all the demand is above the daily maximum *green* available resource, means that the *red* resource was consumed, Figure 7.21.

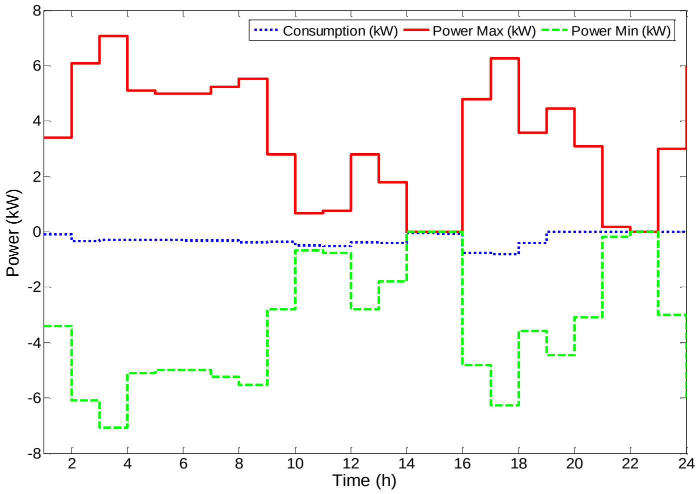

Figure 7.22. Control input profile A_2.

Figure 7.23 shows that the chosen *FLSeq*$_3$ is located here the consumption of red resource is obliged. Due the access order imposed by the auction, the maximum available energy may change hourly, and by this fact the available resource prediction is not as effective as with one house only. Also, the *SL*=1 of both loads of house 3 Table 7.6, is obvious a conditionality and an extra restriction on our optimization algorithm.

The power constrained bounds are respected been the consumed made only when the clean resource is available, Figure 7.24.

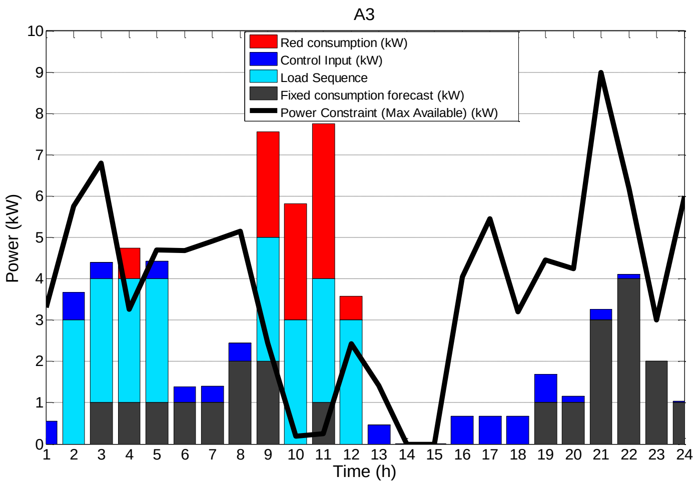

Figure 7.23. Power profile A_3.

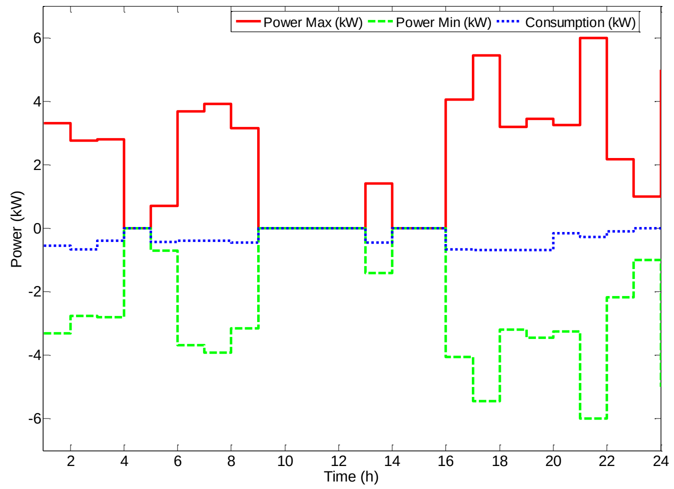

Figure 7.24. Control input profile A_3.

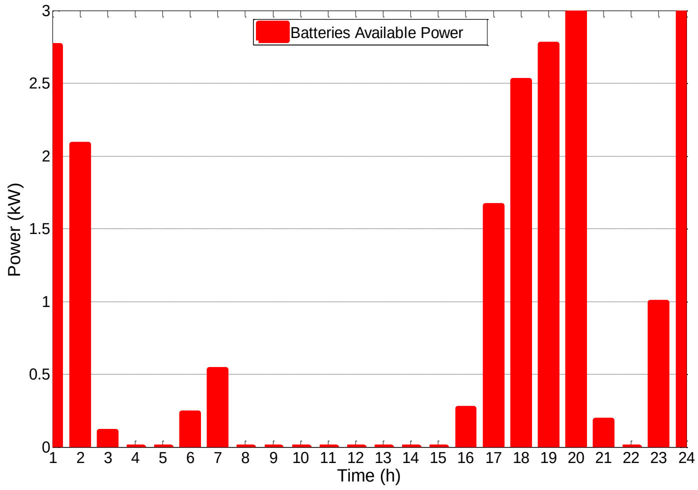

Figure 7.25. Batteries profile.

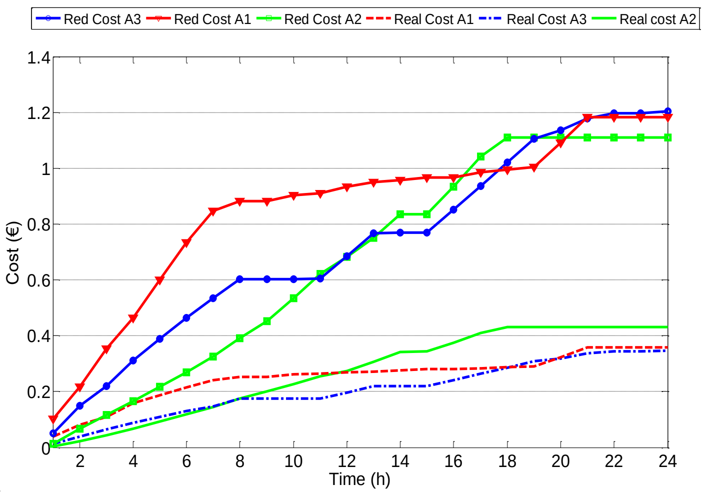

Figure 7.26. Consumption costs.

The batteries profile during the 24h period is show in Figure 7.25. It can be seen that in the most demanding periods, the energy available in the batteries provide a useful energy support. Figure 7.26 demonstrates the advantage of the auction. For each one of the houses it can be seen that the "*Real Cost*" is much lower than the cost of not to bid in auction and only consume the *red* resource "*Red Cost*" at a higher fixed price.

7.4 Conclusions

In this chapter, a distributed MPC control integrative solution was validated in order to provide thermal house comfort in an environment with strong presence of intermittent/limited RES. The approach spots a control problem of multiple subsystems (multi-agent) subjected to coupled constraint solved as a sequence of QP optimization problems for each instant in time.

The approach shows that distributed predictive control is able to provide house comfort within a DSM policy, based in a price auction and the rescheduling of appliance loads. It is a valid methodology to achieve reduction in consumption and price. The approach is more effective with wider periods where the loads are allowed to slide and consequently allocate the most favourable zone.

Chapter 8

Conclusions and Future Work Directions

8.1 Conclusion and Summary of Achievements

It is widely accepted that in a nearby future Smart Grids will be a part of our daily life's. Smart grids will most likely include decentralized generation, active network generation management, energy storage and demand management resources, where the actions of all agents connected to the electricity system can be intelligently integrated aiming for a sustainable, efficient and secure energy supply system. Widespread communications and control technologies required to use DR help maintain the supply-demand balance in electricity systems. Smart household appliances with controllable loads will soon be a common presence in our homes. This active DSM is able to manage the loads to obtain harmony in demand supply ratio, they also include load control manipulation models, pricing, with distinct electricity tariffs along the day, encouraging load management and other approaches which promote energy efficiency and conservation. Many energy consumers are already able to tie the electricity pricing into their energy management system, resulting in greater shifts of energy usage. This needs to be convoyed by the application of intelligent appliances that would facilitate the implementation of DSM.

Therefore, this work intends to be a solution which is able to respond to all this requirements. The work has considered environmental issues and pre-establishes variables as a decision-maker factor. In particular, the work presented a novel multi-agent model-based predictive control method to manage distributed energy resources (DER) systems from the demand side, when in presence of limited energy sources with fluctuating output and with energy storage in household or car batteries. Specifically, the work has presented a solution for thermal comfort which is able to manage a limited shared energy resource via a demand side management perspective, using an integrated approach also involving a power price auction and an appliance load allocation scheme. The control technique has shown to be capable of controlling loads based on the available supply at a certain time, without significantly compromising the user satisfaction.

The developed building's energy management system and smart thermostat feature a lot of programmable settings that allow users and their utilities to maximize energy savings. It is based on a consumer's schedule or peak time's energy demand for the utility; and in a thermostat that pre-programs itself based on weather forecasts to optimize both consumer's energy savings and grid performance. The system uses, weather conditions forecasts and the MPC features to anticipate major changes in weather and manages heating and cooling needs in advance, in the most energy-efficient way.

The term Thermal Control Area (TCA) was presented and described as an entity that is embedded in a distributed environment, where several others TCA's are working individually to achieve their own goal and sharing their information to accomplish a global objective.

An electro-thermal modular scheme was developed to allow an easy building's modelling with different plans where adjacent areas with distinct construction features may thermally interact.

The global scenario described in Chapter 5 present all the basic assumptions in which the work was developed. Also in this chapter the DMPC optimization problem and the Algorithm I which define the implemented basic sequential scheme, were detailed, formalized and exemplified. The obtained results showed its suitability.

In Chapter 6 was presented a solution that solves the problem of control of multiple subsystems dynamically coupled and also stringed to a coupled constraint. Each subsystem solves its own problem by involving its own state predictions, or from neighbourhoods, and the shared constraints. It can be observed throughout the simulations and results analysis that suitable dynamic performances were obtained. The system built in Algorithm II is flexible in two ways. It allows in each auction the agents bid higher or lower in accordance with their needs and, by changing the penalty values during the day, the consumer is able to hourly shift between indoor comfort and lower costs. By knowing in advance the disturbance forecasts, the TCA's are able to make their bid and achieve significant savings at the end of the day.

In Chapter 7, a distributed MPC control integrative solution has been validated in order to provide thermal house comfort in an environment with strong presence of intermittent/limited RES. The developed Algorithm III has shown that distributed predictive control combined with a DSM policy is a tool able to provide thermal comfort, based in a price auction and the rescheduling of appliance loads. It is a valid methodology to achieve less energy consumption and price reductions. The approach has shown to be more effective with wider periods where the loads are allowed to slide and consequently allocate the most favourable zone.

The followed table summarize the implemented features which characterises the developed algorithms.

Table 8.1. Developed algorithm characteristics

Features	Algorithm I	Algorithm II	Algorithm III
Access to *green* energy	**Fixed**	**Variable (hourly)**	**Variable (hourly)**
Distributed nature	**Yes**	**Yes**	**Yes**
Thermal coupling	**Yes**	**Yes**	**Yes**
Information interchange between TCA's	**Yes**	**Yes**	**Yes**
Thermal disturbances	**Yes**	**Yes**	**Yes**
Hourly penalties variability	**No**	**Yes**	**Yes**
Battery storage	**No**	**Yes**	**Yes**
Fixed load allocation	**No**	**Yes**	**Yes**
Priority consumption level	**No**	**Yes**	**Yes**
Sliding load allocation	**No**	**No**	**Yes**

8.2 Recommendations for Future Work Directions

In order to efficiently allocate resources to facilitate balancing of both electricity and heat it would be critical to establish some form of RTP arrangement so users could be fully informed about the value of heat and electricity at each point in time (and location). This would also encourage development of appropriate demand side solutions. This will require introduction of much more sophisticated energy metering (e.g. half hourly metering) and trading functions and would lead to deployment of information and communication systems to ease control of generators and loads. The philosophy of liberal markets assumes economic optimums can only be achieved through negotiations in a free market environment. Because energy is a complex commodity, a sophisticated commercial structure is necessary to make possible the trading between each generator or consumer and purchasers of energy and adjuvant services.

A market with hundreds of thousands or even millions of active participants is clearly a major challenge. All participants will need to access various markets to set up long and short term energy transactions, secure access to the network and provide ancillary services to operate the system in a satisfactory manner (if this is to be done in heat energy, heat networks which would facilitate operation of markets for heat would be required). In order to smooth trading of energy among a very large number of distributed generators and loads, an electronic energy market system, supported by the internet, would be needed to be developed.

RES forecasts of long-term power variation should be considered for a future task. As a rational assumption, it is presumed that RES forecasts are within a short error band, negligible for predicting horizons of 24 hours, but should be estimated for the effect of power variation during longer periods.

Typically, distributed RES fluctuations are counter-balanced by the use of battery storage systems. However, battery systems not only increase the size and cost of RES power systems but also power fluctuations have the effect of reducing the useful life-time of the battery storage system. The use of the battery storage system can, therefore, be fully optimised, minimising storage requirements, avoiding damage to the battery bank and reducing power fluctuations with the consequent useful life of the battery extent . These issues are key topics for future work.

Grid losses were also not considered in this work, they depend on the specific conductors, the current flowing and the length of the transmission line. However, this work has considered distributed resources that, when compared with typical grid framework, reduce the required net inflow from the grid, reduce grid current and hence the grid losses. Thus, in future works grid losses should be considered. To account for actual grid capacities and losses, larger-scale simulations based on the grid network models should be applied to enable an effective analysis of grid stability.

Recent software applications like Google Now (Google Now, 2012) provides an mechanism that is able to inference about the users habits and suggest what is best at the right time, the technology proactively delivers to users information that it predicts (based on their search habits) they may want. Thus, based on the consumer habits, a future approach should take in consideration this type of tool, to advice, in real time the user about consumption measures that can be taken in to account to increased efficiency and reduce energy costs.

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